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Regional labour market mobility. A network analysis of inter-firm relatedness

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Abstract
Labour market rigidity is known to hamper the proper adjustment of an economy, thus, making it less resilient to shocks. This paper investigates the characteristics and resilience of the regional labour flow network in Veneto, a region famous for its industrial districts and the expertise of its workforce. A unique database of inter-firm worker mobility is used and the made-in-Italy relatedness to other industries is quantified. Descriptive results suggest that permanent-contract workers are more mobile within-sector than fixed-term contractors. The latter are more mobile across sectors. A finer disaggregation of the made-in-Italy industries shows that textile, food and woodwork are highly related to leisure-retail, logistics-wholesale and agriculture. These results can orient policy-making in getting faster labour reallocation. Network analysis establishes a number of stylised facts about labour flow networks, in particular, a hierarchical organisation of flows and a preference for workers to move from low-connected to high-connected firms and vice-versa, i.e. disassortativity. Unlike previous research, this paper identifies clusters of a non-spatial nature, that are, based on the intensity of labour flows. Regression analysis shows that labour mobility, both in and out, is beneficial for firms. However, being located inside labour clusters negatively affects firm performance. Interestingly, when these clusters include MNEs, they benefit. These results combined suggest that variety of connections prevails over standardisation.

Keywords
Labour mobility, network analysis, skill-relatedness, cross-industry linkages

JEL Codes
J24, J62, L14, R23, F23

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1. Introduction

Labour immobility is often blamed for perduring unemployment crisis and, thus, hampering the smooth structural adjustment of an economy when faced with shocks. To picture this situation, Zimmermann (2005) calls the rigid labour market of the European Union as eurosklerosis when he compares it to its American counterpart. Labour mobility is geographical when workers move across physical space and occupational when workers move across a set of jobs or sectors. At the aggregate level, both play an important role in shaping the industrial structure: geographical mobility allows the exploitation of resources in new physical space and occupational mobility allows the reallocation of resources to uses that are more productive and the creation of new ventures intra or across sectors. Specifically, higher mobility contributes to the quality of matching between demand and supply of labour.

At the micro-level, recent literature points to the crucial role played by labour mobility, namely, as a conduit of knowledge. Knowledge gets embedded in workers through their qualifications and experience and when they transfer from one firm to another, they bring along their knowledge-base that may or may not be transferred to the hiring firm (Fornahl et al., 2004). As such, worker mobility contributes to the diffusion of knowledge. The mobility of labour is often geographically constrained as evidenced by numerous studies that assume or show that intra-cluster mobility tends to be higher than inter-regional mobility (Malmberg and Power, 2005). Consequently, knowledge diffusion is also spatially constrained. As Keilbach (2012) argues, it is the spatial dimension of knowledge spillovers that lies behind the formation of industrial districts whereby moving inside a certain region facilitates access to that region's stock of knowledge as compared to being outside that region. The spatial configuration of economic activities is, thus, driven by knowledge spillovers.

Many studies have successfully explained the effects of and acknowledged the importance of knowledge spillovers. The transmission of "knowledge" and ideas from one firm to another can, in turn, stimulate the creation of new knowledge and lead to innovation. The organisational learning literature stresses the capacity of firms to absorb knowledge through investment in R&D (Cohen and Levinthal, 1990). However, little research has been done on the conductor of such knowledge, namely, the specific process of accessing knowledge that usually occurs inside a network arrangement (Tsai, 2001).

The present research builds on the tenets that knowledge spills across firms through labour mobility[1]. Therefore, one of the aims of this research is to investigate the dynamics of local labour flows in the Veneto region, thereby allowing one to make inferences on the trajectory of knowledge flows. In particular, it investigates the characteristics of mobile workers in terms of their skills, qualifications, experience, type of work contracts and other demographics. It uses a unique database of individual worker employment records kept by the Ossevatorio and Ricerca unit of Veneto Lavoro Institute. This research ranks the relatedness of the made-in-Italy (MI) industry to other industries by calculating the intensity of inter-industry labour flows. Sectoral labour flows are confronted with worker characteristics.

To achieve these aims, this research uses an intuitive model to analyse flow data, that is, social network analysis. This approach allows the mapping and debunking of complex relationships, such as, interactions that occur in protein networks and interna-

[1]It is not claimed that labour mobility is the only source of knowledge spillovers. See Audretsch & Feldman for different sources of knowledge spillovers

tional trade networks to name a few (Borgatti et al., 2009). The structural properties of labour flow network (LFN) can provide insights into the dynamics of labour flows and the resilience of the network; in particular, the fluidity of labour mobility and the direction of knowledge flows can be assessed. This paper establishes a number of stylised facts about LFNs: the presence of few firms with disproportionately high labour mobility, ie. long-tailed distributions; the hierarchical structure of the network; the disassortative nature of firms' connections; and, the small-world nature of LFN. It also shows that the structure of labour mobility is not the interplay of a pure random process but involves organisation. Network statistics grouped by sub-industries reveal sectoral differences.

This research contributes to a better understanding of MI industry; an industry that acts as the backbone of the Italian economy, securing employment to many. A popular definition comprises of the traditional food, fashion, furniture but also the more modern mechanical engineering. In the present paper, MI groups together sub-industries that produces primarily finished product, namely, Ceramics, Eyewear, Food, Footwear, Glass, Jewellery, Marble, Tanning, Textile-clothing, Wood-furniture and Other miscellaneous industries. In Veneto, MI is the second largest industrial employer behind Metalworks, and is the fourth in all sectors with Services-to-the-person and Leisure-retail sectors occupying the leading positions[2]. This work analyses the network properties of MI industry and ranks its relatedness to other sectors.

Given the hierarchical nature of this LFN, this research uses a novel algorithm to identify clusters that are defined as a group of firms between which labour flows are intense. Thus, it departs from previous studies in that it views clusters as agglomerations of skills and knowledge instead of taking the localised view of inter-related firms bounded by space (Malmberg and Power, 2005). This exercise aims to assess whether the sector relatedness identified previously are recurrent in intensely connected labour clusters. Many of the results are confirmed, thus, supporting the point that inter-firm labour mobility reflects industry-relatedness as far as skill-profiles are concerned. By using this approach, this research fills in a gap that exists in agglomeration studies in which extra-local linkages are often overlooked as the focus is on a bounded space. Note that extra-local linkages can mitigate the effects of cognitive and sectoral lock-in through the inflow of knowledge from outside the local area (Boschma, 2005). Indeed, the empirical analysis shows that firms connected to a variety of other firms have improved performance whereas firms embedded in standardised or localised connections are negatively affected.

Multinationals (MNEs) can be a good source of extra-local knowledge as they are less likely to be influenced by the local dynamics. Indeed, research finds that workers that have MNE experience contributes significantly to productivity improvements in the non-MNE firm which recruited them (Balsvik, 2011). A major aim of this research is to assess the role of multinationals (MNEs) in the MI labour networks. The use of a comprehensive database, Reprint Italia Multinazionale[3], allows the identification of foreign MNEs in Veneto and, hence, in labour flow clusters. Independent samples t-test with unequal variances confirms that MNEs are more connected than the rest of the firms. Econometric analyses reveal that the presence of MNEs in labour flow clusters improve the performance of firms located in these clusters.

Since the knowledge of skill-related industries ex-ante can help in predicting labour flows, this research contribute to socio-economic regional policy-making: the informa-

[2] Author's own calculation, see Table A1 in the Appendix

[3] See section Data sources

tion about the relatedness of industries could be useful for redeployment strategies, particularly in periods of economic restructuring when some sectors decline and others flourish. Although Veneto is popular for its tourism resources, it is a heavily industrial region and strongly export-oriented. Since the last economic crisis, it has become increasingly vital for its industries to maintain and improve their international competitiveness in order to prevent their exit from the international market. Previous research on this topic, i.e., Veneto labour networks, use data up to the year 2000 (for instance (Gianelle, 2014)). This research uses recent data that fill in the gap that exists on this topic and, thus, cover patterns that emerge in the post-crisis period.

The following section reviews the literature on labour flow networks and knowledge spillovers. Section 3 provides details about the data sources and the descriptive statistics. It also undertakes a sectoral analysis of labour flows taking into account worker characteristics. Section 4 documents the structural properties of the MI labour flow network and establishes a set of stylised facts. Moreover, clusters are identified and investigated. Section 5 uses econometric analysis to investigate the role of firms' connectivities and the role of MNEs in firms' performance. The last section concludes and discusses the implications for policy.

2. Background literature

2.1. *Labour market fluidity and knowledge diffusion*

The recent economic crisis has increased interest in systems that are resilient to changing economic scenarios, that is, systems that can quickly and smoothly absorb shocks and reconfigure themselves so as not to self-destruct. Because of its wide socio-economic implications, the resilience of labour markets has been highlighted by policies and made the subject of recent studies (Diodato and Weterings, 2015). Market forces lead to the creation, destruction, expansion and contraction of firms together with the creation and destruction of jobs. This process leads to a reallocation of jobs and workers between firms and sectors. Such reallocation is inevitable and necessary in a market economy whereby resources should move from less efficient to more efficient uses; ultimately, reallocation contributes to productivity and output growth.

However, some countries experienced a decline in labour market fluidity over time. Hyatt and Spletzer (2013) attributes the diminishing employment dynamics of the US to the loss of short-term jobs where such periods of decline usually occur during recessions without expanding thereafter. According to Davis and Haltiwanger (2014), this decline, in terms of both worker and job reallocation, is pervasive across states, industries and demographic groups. The authors also acknowledge that low labour market fluidity may have some benefits, for example, fewer jobs being destroyed such that fewer workers lose their jobs and, thus, reducing unemployment. Such a declining trend started in the 1980s and the authors point to some of the reasons for concern. Firstly, low fluidity implies less new jobs on the market; this translates into longer unemployment spells and less chance of moving up the job-ladder, changing careers or moving location for the employed. Secondly, firms find it more difficult to hire and fire due to rigidity of the system. Thirdly, the economy as a whole may experience increased unemployment, wage lock-in and decreased productivity. The economy becomes less dynamic and less responsive to shocks.

At the micro level, firms also benefit from higher labour market fluidity. Higher worker success and technological progress, especially in a cluster setting, improve firms' performance. Firms that rely on the quality of their human capital and knowledge-intensive technologies benefit considerably from increased mobility (Power and Lundmark, 2004). Eriksson and Lindgren (2009) compares the extent of diffusion of knowledge that happens through economies of co-location, diversity and scale with that brought in by labour mobility. They find that the latter has a stronger effect. Thus, labour mobility is a key channel of knowledge spillovers. Maliranta et al. (2009) uses Finnish employer-employee data to assess whether a firm's R&D efforts bring benefits to hiring firms in terms of increased productivity. They found strong evidence of knowledge spillovers. But hiring from other firms' R&D labs to their own non-R&D labs was a more statistically significant channel of knowledge spillovers than hiring workers into their own R&D labs. This result points to the relevance of *diversified* experience which can be extended to inter-sectoral mobility.

Workers that have experience in productive firms are more "knowledgeable" and other firms can have access to this superior knowledge by hiring these workers. Indeed, close in geographical scope to this present research, Serafinelli (2015) uses Venetian social security earnings records coupled with balance sheets data to show how labour mobility between firms leads to knowledge spillovers. First, high wage firms are shown to be more productive; second, non-high wage firms are shown to experience increases in their productivity level (0.14 to 0.28 per cent) when they employ "knowledgeable" workers who had recent experience at a high wage firm as opposed to non-high wage firms that do not employ "knowledgeable" workers.

However, firms also incur the costs of high labour reallocation rate, mainly, increased recruiting costs. High labour turnover usually discourages firms to invest in training their personnel and, as such, the stock of skilled labour pool suffers (OECD, 2009). While high labour mobility involves a negative incentive effect, Cooper (2001) reports that it does not necessarily hinder investment in R&D. Nevertheless, workers incur higher search costs. The present paper draws from the literature that labour mobility implies knowledge spillovers. Given the increasing role of knowledge in contemporary economies, it contends that higher mobility increases an economy's resilience. It aims to assess the degree and extent of the MI labour market fluidity so as to infer the resilience of the Veneto region.

2.2. *Clusters and diffusion of knowledge*

Many studies report that spatial proximity tends to enhance the spread of knowledge and facilitates innovation through short cognitive distance, trustful relations, easy observation and comparison. Thus, Malmberg and Power (2005, p3) points to the "distinctly localised component" of the industrial system. However, reviewing the cluster literature, these authors find that localised inter-firm collaborations, be it transaction-based (e.g. buyer-supplier relationships) or not, are not the driving force behind the creative ability of clustered firms. Contrarily, much of firms' links are extra-local.

While there is limited inter-firm direct interaction within clusters, there seems to be a concentration of specialised skills inside clusters as reported by Lissoni (2001). This idea is well-elaborated in studies dealing with labour market pooling as agglomeration economies. For instance, Melo and Graham (2014) finds evidence of a positive relationship between agglomeration economies and the quality of employee-employer matching suggesting labour market pooling in England and Wales. Previously, Gabe and Abel (2012) finds that occupations with similar knowledge profiles and specialised contents often co-agglomerate. Moreover, Dahl (2002) shows that inter-firm mobility of Danish engineers is higher within a set of two defined clusters than elsewhere and, the fact that their wages are higher in the hiring firm is an indication of positive knowledge spillovers.

Given the importance of clusters for the flow of knowledge, this research investigates the presence and content of clusters in the Venetian MI labour market. It departs from traditional studies of clusters as it takes a non-localised (spatial proximity) view of clusters to identify clusters. Instead, emphasis is laid on economic proximity by focusing on relational networks, in this case, labour flow networks. This does not mean that spatial proximity is neglected as a determining factor. It contends that firms with similar knowledge profiles, in other words, skill-related firms are linked by more labour flows than unrelated firms.

2.3. *MNEs and knowledge*

In the age of global value chains, the role of MNEs in host and home country is a highly researched topic and a number of studies have focused on their impacts. It is also acknowledged that working in MNEs provides exposure to rich knowledge and information that differs from the internal context. The introduction of external knowledge prevents inertia or lock-in that often happens within a localised learning boundarry. But fewer studies look at the knowledge that workers accumulate while they are involved with an MNE and that they consequently transmit to local hiring firms (Poole, 2013). In such a study, Ebersberger et al (2011) uses Finnish labour mobility data for the period 1995 to 2004 and shows that firms that hire from MNEs have increased innovation activities and success whereas firms that hire from uninationals experience a decrease in innovation activities and success. The paper shows that high labour mobility has a stronger positive impact on innovation activities when the hiring firm is uninational firms than when it is an MNE. It argues that higher mobility enlarges the competence base of national firms.

Balsvik (2010) finds robust evidence that labour mobility is a channel of knowledge diffusion in Norvegian manufaturing. He finds that worker flows from MNE to non-MNE bring about 20 percent more to productivity as compared to workers without MNE experience. Moreover, previous MNE workers receive a higher wage premium in the non-MNE hiring firms. The author concludes that this result provides evidence for the higher value that firms attribute to knowledge coming from MNEs. One of the objectives of the present research is to assess whether MNEs locate in highly-skilled labour flow clusters and whether they benefit from this strategic localisation.

2.4. *Labour flow networks (LFN)*

In recent decades, it has become increasingly popular to model complex systems as networks; from the detection of terrorist cells (Masys, 2016) to trade through protein-protein interaction networks (Borgatti et al., 2009). One of the allures of representing a problem as a network is that it enables one to see beyond individual elements and to dig into their connectivities. The interplay of multiple interacting elements can be seen from a global perspective enabling the researcher to observe the effects of shocks, both direct and indirect, into the system and, particularly, the transmission of these shocks from one element to another and beyond. The motivation for analysing the LFN as a network lies in its ability not only to analyse worker flows from firm x to y but also to take into consideration firm z (and others) in the picture. Thus, it can highlight the interdependence of firms to a common pool of labour.

A network is a collection of nodes connected by links. In the LFN case, employers/firms are the nodes and labour flows between any two firms represent the links. The presence or not of a link with another firm is useful in understanding the web of labour flows. When such relations are of a binary nature (onle the presence or not of a link is accounted for), the network is called a binary network. Weighted network also takes into account the intensity of a link. In the LFN, a link l is defined whenever a worker moves from firm i to firm j in time period t, $l_{ij}^{t} > 0$ and $i \neq j$. Moves from firm j to i is also accounted for, thus, the network is a directed one.

Recently, Guerrero and Axtell (2013) investigates the topological properties of the Finnish labour flow network for the period 2005-2008. The paper shows that the degree distribution (the probability that a node chosen at random has a certain number of links) of the Finnish LFN is heavy-tailed, as is the case for many other social networks (Barabási and others, 2009). Heavy-tailed distribution implies that a few firms have very high degrees while the majority of firms have very low degrees. Most of the statistical patterns results are robust to comparison with the Mexican LFN, in particular, both countries' LFNs have heavy-tailed degree and labour flow distributions. Moreover, both LFNs have their clustering coefficients correlate negatively with their degrees—evidence of a hierarchical structure. Clustering coefficient is seen as a measure of the structural importance of firms. Assortativity, that is, whether a firm tends to connect to other firms that have the same number of connections as itself, is measured. Contrarily to most social networks that are assortative, both LFNs were disassortative but the Finnish network shows disassortativity after 35 connections.

In the same spirit as this research, Gianelle (2014) uses Veneto worker histories database derived from records of the Italian social security institute (INPS) for the time-period 1990-2000 to analyse the small world property of the Veneto LFN. The database only includes private employers and employees. The present paper do not exclude labour flows to and from the public sector. Gianelle (2014) concludes that the Veneto labour network exhibits small-world properties, that is, each firm can be reached by every other firms through just a few steps. The average number of links per firm is about 10 while the median is just 2. Just as for Finland, the degree distribution of the Venetian LFN converges to power-law at very high quantiles. The author identifies the presence of a small number of highly connected hubs where hubs are simply the top 50 firms with the highest number of total degree. The author claims that the presence of hubs makes the network vulnerable as the failure of a few hubs would divide the market in distinct parts. While this is a valid argument, it puts too much emphasis on quantity of links. Hubs may have many connections but whether they disrupt a market would depend on their strategic centrality in the network or whether they are in highly connected clusters. In this research, this lacuna is addressed by using a novel algorithm to identify clusters of highly connected firms.

3. Data source and description

This research derives its data from a database maintained by the research unit of the Veneto Lavoro institute (Osservatorio & Ricerca) that keeps track of all regular employment contract that occurs inside the Veneto region detailing the type of contract, qualification, education, employment duration, age, sex and nationality of the employee. It also records the employer's characteristics such as number of workers, sector in which it operates, legal status and a few other variables of interest. Note that only individual worker employer-to-employer flows can be observed; unemployment spells are not accounted for and first-time employment cannot identified. To identify MNEs within the Veneto Lavoro database, the Reprint Italia Multinazionale database, developed by R&P (Ricerche & Progetti) and Politecnico di Milano is also used[4]. To perform the empirical analysis, measures of firms performance are retrieved from AIDA (Analisi Informatizzata Delle Aziende), a database that maintains Italian company records and business intelligence.

The period under study is from the beginning of year 2012 to the end of year 2013. This 2-year period is chosen as, firstly, it is long enough to observe relevant number of flows and, secondly, a 2-year period gives job hoppers reasonable amount of time to find new employment, thus, the results might be useful for policy. As shown in Table 1, there is a total of 47706 unique firms/employers that experience labour movements out of a total of 330409[5] registered firms, roughly 14 percent, for the period under study. There is a total of 95356 worker flows to and from the MI sector; flows within a single firm, for example, when a worker obtains a promotion and signs a new contract with her current employer, are excluded as it does not add to the object of this study. When the same worker moves more than once, each movement is counted as a flow. For the period under study, more firms are firing, 32508 firms, than hiring, 29439 firms. On average, 1.2 workers move from firm i to j with a standard deviation of 1.5; the distribution of flows is very skewed (the results are not shown here). More than 91 per cent of cases involve just one worker flow per firm and about 5 per cent involve 2 worker flows. Nonetheless, the number of flows range from 1 to 155.

A simple measure of worker mobility, F, is the ratio of mobile workers m to the stock of workers employed n, in time period t, that is, $\frac{m^t}{n^t}$. Here, the stock of workers n refers to all workers employed in MI firms and from firms that experienced a flow with an MI firm, averaged for the years 2012 and 2013. Thus, labour to and from MI sector is about 12% mobile; when only movements to and from multinational firms (MNEs) are considered, mobility is 9%. From now on, whenever the term mobility is used in this paper, it refers to flows weighted by size.

While the majority of workers that change employers have permanent work contracts, they are the least mobile workers in terms of the flow-to-stock ratio (4%). Workers on a staff-lease contract are by large the most mobile group (206%); the latter are workers employed by a third-party, for example, a job agency, to work in a firm with which the third-party has a contract. Job agencies appear to play a significant role in facilitating labour mobility. Internships and domestic contracts are the next two most mobile contract types; domestic contracts in Italy are specific to cleaners and caregivers. Usually, these workers try to accumulate work experience and are necessarily mobile. Moreover, these contracts are of short duration so that workers are compelled to find new jobs opportunities if their contracts are not renewed. The less mobile workers are those with the most stable contract, i.e, the permanent contract. Surprisingly, those on a fixed-term contract are more mobile than those with an on-call contract. This could be due to the higher skills of the former group but, on the contrary, 77% of workers with an on-call contract are high-medium skilled compared to only 59% of workers with fixed-term contract in 2012 (See Table A2 in Appendix).

Workers' qualifications are categorised as:

- High-skilled: managers/directors, intellectual professionals, technical professionals

[4] http://www.repnet.it

[5] See Appendix

Table 1. Flows and mobility by worker categories, all firms, and MNEs

	Total number of firms: 47706					**Number of MNEs: 227**			
	Flows	**Mean**	**SD**	**%**	**F**	**Flows**	**Mean**	**%**	**F**
Total Flows	95356	1.2	1.5		12%	1808	1.2		9%
			WORK CONTRACTS						
Permanent	26586	0.3	1.1	28%	4%	356	0.2	20%	2%
Apprenticeship	4037	0.1	0.2	4%	14%	47	0	3%	14%
Fixed-term	25156	0.3	0.9	26%	32%	389	0.3	22%	43%
Staff-lease	24299	0.3	0.9	25%	206%	727	0.5	40%	107%
On-call	4793	0.1	0.3	5%	19%	71	0	4%	241%
Domestic	1462	0	0.1	2%	69%	16	0	1%	533%
Project-based	2081	0	0.2	2%	10%	64	0	4%	36%
Internships	6942	0.1	0.3	7%	71%	138	0.1	8%	150%
			SKILLS						
High-skilled	9201	0.1	0.4	10%	5%	296	0.2	16%	5%
Medium skilled	23749	0.3	0.6	25%	9%	446	0.3	25%	13%
Low skilled	45263	0.6	1.4	47%	20%	706	0.5	39%	9%
Unskilled	16987	0.2	0.7	18%	15%	352	0.2	19%	16%
			AGE						
Less than 30	35061	0.4	0.8	37%	24%	763	0.5	42%	28%
More than 30	60295	0.8	1.2	63%	9%	1045	0.7	58%	6%
			EDUCATION						
No education	8493	0.1	0.6	9%	29%	27	0	1%	9%
Compulsory	40842	0.5	1	43%	15%	603	0.4	33%	10%
Diploma	37412	0.5	0.8	39%	12%	863	0.6	48%	11%
Graduate	7741	0.1	0.4	8%	7%	296	0.2	16%	9%
			SEX						
M	50276	0.6	1.1	53%	12%	1022	0.7	57%	8%
F	45080	0.6	1.1	47%	12%	786	0.5	43%	12%
			WORK SHIFT						
Full-time	59372	0.8	1.3	62%	11%	1344	0.9	74%	8%
Part-time	29260	0.4	0.9	31%	18%	320	0.2	18%	36%
			NATIONALITY						
Italian	67195	0.9	1.1	70%	10%	1504	1	83%	9%
Non-Italian	28161	0.4	1.1	30%	25%	304	0.2	17%	17%
			EMPLOYMENT DURATION						
Less 1 year	69849	0.9	1.2	73%	40%	1345	0.9	74%	58%
1-3 years	11658	0.1	0.6	12%	8%	203	0.1	11%	7%
Over 3 years	75	0	0	0%	0%	2	0	0%	0%

Only firms that experience a worker flow either in or out for the period 2012-2013 are presented here.

- Medium-skilled: office staff, services professionals
- Less-skilled: skilled workers and semi-skilled workers
- Unskilled

In general, low-skilled workers are more mobile and so are those without a formal education and those that are less than 30 years old. These results may suggest that workers without education, skills and experience tend to obtain jobs of a temporary nature forcing them to be mobile. Note that graduates are more mobile with MNEs compared to all firms while those with no education are less mobile with MNEs.

Men and women are equally mobile although men are more in numbers. Interestingly, women are more mobile in MNEs. Neophytes with less than a year with the source firm are highly mobile (40%) while those with more than 3 years with an employer are not mobile. The immobility of the latter group is probably due to the fear of skill loss and, consequently, wage loss. It is known that there is a high probability of losing skills (hence, wages) when one separates from one's current job and lands in a new occupation that requires a new set of skills (Fujita, 2015). Italian nationals have a low mobility compared to foreigners and this result holds for the case of MNEs. More than 30 per cent of all mobile workers have a part-time contract but only 18 percent in MNEs.

3.1. ***Sectoral analysis of labour flows and industry relatedness***

3.1.1. Where do MI labour come from and where do they go?

This question is useful in that it allows the measurement of the MI industry skill-relatedness with other industries. It is implied that the more exchange of labour occurs between two industries, the more their labour share similar skills (Neffke and Henning, 2012). It is a revealed measure of skill-relatedness (industry relatedness) which can be useful to predict the trajectory of labour flows and orient policy-making decisions. Flows are categorised by sectors: initially, 13 sectors are used that corresponds to the ateco2 of the original Veneto Lavoro database.

Table 2 shows flows of all workers to and from the MI sector: the third row indicates that 1858 workers from the agricultural sector joined MI (3% of all workers that moved to MI) and 2590 MI workers joined agriculture (4% of all workers that left MI). Overall, the MI sector shrank as more workers left the MI sector than joined it, a total of 64781 to 57888. This decline is probably due to industrial restructuring following the economic crisis of the past years where many activities that were integral part of manufacturing before are now taken over by manufacturing-related industries. This issue has led scholars from the Manufacturing Metrics Expert Group to question the appropriateness of current metrics as they find that there are 1m pre-production jobs and 1.3m post-production jobs that support traditional manufacturing jobs in the UK in the year 2010 (IfM, 2016). Interestingly, only 42% of MI workers move within the sector. But an impressive 15% move to and from the Leisure-retail sector. Similarly, 8% of workers move to and from Logistics-wholesale and another 8% to and from Metalworks-engineering. Surprisingly, 11% of workers that left MI found employment in Serv.-health-edu (Health, Education, Services-to-the-person, Public administration) sector.

In order to mitigate the effect of large firms and sectors that would necessarily experience more labour churning, labour to employment ratio, i.e., labour mobility F_i for each firm i is calculated and then summed by sector. The percentage for each sector is reported under column W in Table 2 and in all subsequent tables. The weighted results confirm the absolute results that inter-industry mobility is as important as intra-industry mobility; a result that is contrary to established thinking that within-industry mobility is easier and pervasive. The strong inter-sectoral labour mobility between Leisure service-retail and MI is also confirmed. Industry-relatedness, *Relatedness*, is calculated by averaging to and from mobility $\frac{W_{in}+W_{out}}{2}$ and a ranking of the results is provided under the column *Relatedness*. As per this ranking, MI sector is highly related to Leisure-retail, Logistics-wholesale and Health-Education-Personal Services sectors and least-related to Extractive, Utilities and Financial services.

It is suspected that those sectors that are highly-related to MI are along the local value-chain either backward or forward. Further disaggregation of the sectors allows such linkages to be inferred as demonstrated in Section 3.1.5.

3.1.2. Are workers on different type of contracts equally mobile?

Intra-industry labour mobility is often the result of workers moving to improve their economic return, and, thus, to minimise adjustment costs, it is easier for them to move within-sector. Workers with a stable contract that fear skill loss when they switch occupation are also more likely to move intra-sector. Moreover, MI is a sector that requires specific skills and, as such, MI employers are more likely to hire workers that have stable contracts or more experience. Those on short-term contracts may have less

Table 2. Absolute flows and sectoral labour mobility to and from MI sector

From various sectors to MI				From MI to various sectors			
W	**%**	**Flows**	**Sectors**	**Flows**	**%**	**W**	*Relatedness*[a]
5%	3%	1858	**1.Agriculture**	2590	4%	3%	*5*
4%	3%	1732	**2.Construction**	1208	2%	2%	*7*
48%	47%	27323	**2.MI**	27323	42%	50%	
4%	8%	4479	**2.Metalworks**	4828	7%	5%	*4*
0%	0%	20	**2.Mining**	18	0%	0%	*12*
2%	4%	2138	**2.Oth. ind.**	2360	4%	2%	*8*
0%	0%	169	**2.Utilities**	229	0%	0%	*11*
2%	2%	1305	**3.Adv. Services**	161	0%	0%	*9*
0%	0%	149	**3.Financial serv.**	1472	2%	2%	*10*
17%	15%	8490	**3.Leisure-retail**	9646	15%	16%	*1*
6%	8%	4536	**3.Logist-wholesale**	4863	8%	6%	*3*
2%	3%	1982	**3.Oth. serv.**	2839	4%	4%	*6*
10%	6%	3707	**3.Serv.-health-edu**	7244	11%	10%	*2*
		57888	Total	**64781**			

[a]This is a ranking where 1 is the most related.

Table 3. Flows to and from the MI sector: permanent vs fixed work contract

From various sectors to MI					**From MI to various sectors**				***Relatedness***	
Fixed-term		**Permanent**			**Permanent**		**Fixed-term**		***Perm***	***Fixed***
W	Flows	W	Flows	**Sectors**	Flows	W	Flows	W		
4%	819	1%	198	**1.Agriculture**	142	1%	2170	12%	*9*	*4*
4%	593	2%	343	**2.Construction**	326	1%	483	3%	*6*	*7*
39%	5052	68%	13402	**2.MI**	13402	70%	5052	30%		
10%	979	3%	778	**2.Metalworks**	952	3%	960	6%	*4*	*3*
0%	8	0%	3	**2.Mining**	11	0%	4	0%	*12*	*12*
4%	447	1%	400	**2.Oth. ind.**	380	2%	380	3%	*7*	*8*
0%	44	0%	25	**2.Utilities**	54	0%	74	0%	*11*	*11*
3%	306	2%	393	**3.Adv. Services**	45	0%	31	0%	*8*	*9*
0%	40	0%	38	**3.Financial serv.**	313	1%	366	3%	*10*	*10*
19%	2516	12%	1651	**3.Leisure-retail**	1797	10%	3095	18%	*1*	*1*
9%	1256	6%	1081	**3.Logist-wholesale**	1372	5%	1754	10%	*2*	*2*
3%	559	1%	347	**3.Oth. serv.**	716	3%	1078	7%	*5*	*6*
5%	961	4%	1123	**3.Serv.-health-edu**	689	3%	1180	7%	*3*	*5*
	13580		**19782**	**Total**	**20199**		**16627**			

experience and are less likely to succeed in securing jobs within MI compared to those with more stable contracts. It is expected that workers with a stable contract, such as, a permanent contract, are more mobile within-MI than those without a stable contract, such as, a fixed term contract or staff-lease contract. Table 3 reports sectoral mobility of workers to and from the MI sector by contract types: permanent and fixed-term.

As expected, those on a permanent contract are definitely more mobile within the MI (70%) than those on a fixed-term one (30%). Nevertheless, a good percentage of permanent workers, an average of 11% and 6%, moves to and from from Leisure-Retail and Logistics-wholesale respectively. These figures increase much for those on a fixed-term contract: 19% Leisure-retail and 10% Logistics-wholesale respectively. In terms of relatedness, they rank first and second for both permannet and fixed-term workers. This implies strong skill relatedness to these two sectors. Relatedness to Metalworks and Agriculture are more intense for fixed-term than permanent workers. The MI sector recruited and fired more permanent than fixed-term workers. The ratio of fixed-term to permanent recruits into MI is 1:1.5 while that of exits is 1:1.2.

Table 4. Flows to and from the MI sector: high-skilled vs unskilled workers

From various sectors to MI					**From MI to various sectors**				***Relatedness***	
Unskilled		**High-skilled**			**High-skilled**		**Unskilled**		***High***	***No***
W	Flows	W	Flows	**Sectors**	Flows	W	Flows	W		
3%	380	1%	92	**1.Agriculture**	38	1%	1685	14%	*10*	*4*
4%	297	3%	135	**2.Construction**	102	2%	253	2%	*9*	*8*
36%	2077	40%	2066	**2.MI**	2066	38%	2077	19%		
12%	785	10%	618	**2.Metalworks**	725	14%	957	8%	*1*	*3*
0%	2	0%	2	**2.Mining**	7	0%	1	0%	*12*	*12*
7%	397	4%	263	**2.Oth. ind.**	379	7%	475	4%	*5*	*7*
0%	33	0%	15	**2.Utilities**	27	0%	86	1%	*11*	*11*
3%	117	10%	371	**3.Adv. Services**	41	1%	15	0%	*6*	*9*
0%	10	1%	36	**3.Financial serv.**	530	8%	143	1%	*7*	*10*
9%	918	10%	826	**3.Leisure-retail**	468	8%	1127	6%	*3*	*6*
13%	695	14%	607	**3.Logist-wholesale**	579	10%	1231	10%	*2*	*2*
7%	403	5%	171	**3.Oth. serv.**	139	2%	1160	8%	*8*	*5*
5%	508	3%	249	**3.Serv.-health-edu**	714	10%	3232	26%	*4*	*1*
	6622		**5451**	**Total**	**5815**		**12442**			

3.1.3. Are workers with different skills equally mobile?

Table 4 shows the sectoral mobility of high-skilled and unskilled workers. Theory suggests that high-skilled workers are more mobile than low-skilled ones. In reality, it appears that the issue is much more complex when comparing mobility of skilled-unskilled for a particular industry or across industries. For some industries, for example, Logistics-wholesale, Utilities and Construction, both groups are equally mobile. However, there is a difference in skilled-unskilled relatedness for other industries. If only the unskilled workers are considered, the most related industry to MI is Services-to-the-person, Health, Education. As regards the highly skilled, the most related industry is Metalworks-engineering. Nevertheless, both sectors are amongst the top ranked together with Logistics-wholesale; a result that further accentuate the relatedness of these sectors shown in the type of work-contracts analysis in the previous section. As one would expect, Advanced services is better related to MI for the high-skilled than for the unskilled. Contrarily, the relatedness of Agriculture to MI is more relevant for the unskilled. Interestingly, besides Metalworks and Logistics, high-skilled Leisure-retail workers are more related to MI than most other industries that one would traditionally thought of as being related.

These results suggest that different sectors use different levels of skills and this renders both groups quite mobile. High-skilled workers intra-MI mobility is slightly higher than that of unskilled. The ratio of unskilled to high-skilled recruits is 1:0.8 and the ratio for exits is 1:0.5. However, the total number of unskilled workers that left the MI sector is twice as more than the high-skilled workers that left the sector. It appears that the MI sector is selecting into skilled workers rather than unskilled ones.

3.1.4. Do different educational levels matter for mobility?

Does education play a role in sectoral mobility of MI employees? In today's skill-intensive economy, the demand for uneducated workers is usually low or only of a temporary nature. Moreover, workers with low education usually find it difficult to keep their jobs and are, thus, constantly on job search. These two features make the low-educated more mobile. The demand for those having a tertiary education is usually high making them more likely to be mobile, particularly across sectors. Table 5 compares labour mobility of those who have a degree education to those who do not have a formal education. On the one hand, while the most mobile group of workers is those with no education, they mostly move within the MI sector; they are largely immobile

Table 5. Flows to and from the MI sector: Degree holders vs No education

From various sectors to MI					**From MI to various sectors**				***Relatedness***	
No edu.		**Degree**			**Degree**		**No edu.**		***Deg.***	***No***
W	Flows	W	Flows	**Sectors**	Flows	W	Flows	W		
2%	162	3%	117	**1.Agriculture**	112	3%	263	3%	*9*	*5*
1%	72	2%	75	**2.Construction**	63	2%	49	1%	*10*	*8*
71%	5006	25%	1131	**2.MI**	1131	24%	5006	71%		
2%	136	8%	418	**2.Metalworks**	466	9%	172	3%	*4*	*4*
0%	0	0%	2	**2.Mining**	4	0%	1	0%	*12*	*12*
1%	75	3%	175	**2.Oth. ind.**	212	4%	57	1%	*8*	*7*
0%	3	0%	20	**2.Utilities**	21	0%	7	0%	*11*	*11*
0%	15	9%	361	**3.Adv. Services**	54	1%	1	0%	*5*	*10*
0%	2	1%	59	**3.Financial serv.**	377	7%	20	0%	*6*	*9*
6%	284	28%	1033	**3.Leisure-retail**	787	19%	394	7%	*1*	*2*
3%	196	11%	473	**3.Logist-wholesale**	495	12%	175	3%	*2*	*3*
1%	110	4%	153	**3.Oth. serv.**	187	4%	140	2%	*7*	*6*
14%	645	6%	329	**3.Serv.-health-edu**	616	15%	506	9%	*3*	*1*
	6706		**4346**	**Total**	**4525**		**6791**			

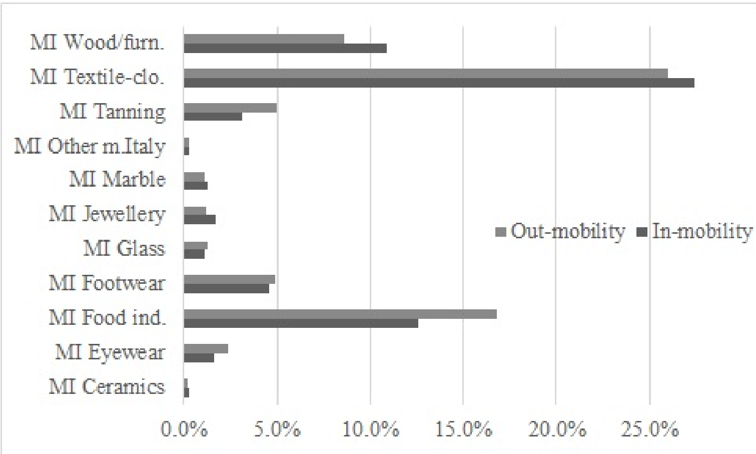


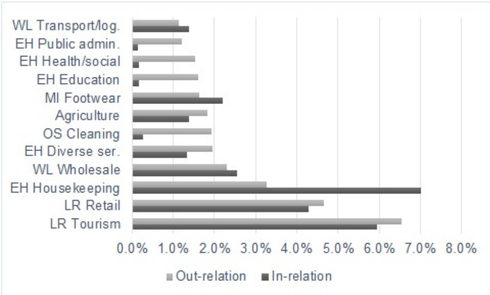
Figure 1. Percentage of MI sub-industries total in and out labour mobility to all other sectors

outside MI except for Services-to-the-person, Health, Education. This result concurs with the employment polarisation literature which reports the growth of low-skilled service occupation (Autor and Horn, 2013). On the other hand, while those with a degree education are less mobile in total, they are more mobile across a wide range of sectors. For instance, degree educated from Leisure-retail sector are more mobile than degree educated within MI. Marked differences exist in relatedness between degree and uneducated workers for Advanced tertiary and Financial services.

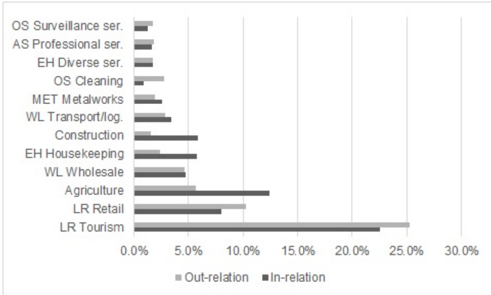
3.1.5. Second level disaggregation of relatedness and inter-sectoral mobility

In this section, the sub-sectors above are further disaggregated into 45 sub-industries including 11 MI sub-industries, namely, ceramics, eyewear, food, footwear, glass, jewellery, marble, tanning, textile, wood-furniture and other MI. When mobility within the same sub-industry is excluded, the most related sub-industry from which MI recruits is Tourism-leisure. It is followed, in order of relatedness, by Housekeeping, Retail, Agriculture Construction and Wholesale (See Table A3 in the Appendix). Note how Housekeeping is more related to MI than Retail, a detail that is hidden in the aggregated analysis. The most related industry which MI workers join is Tourism followed by Retail, Wholesale, Agriculture, Housekeeping and Metalworks.

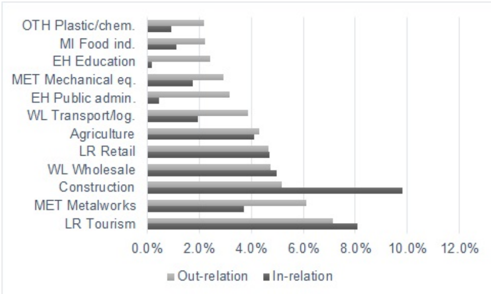
Figure 1 graphically compares the in- and out-mobility of the 11 MI sub-industries



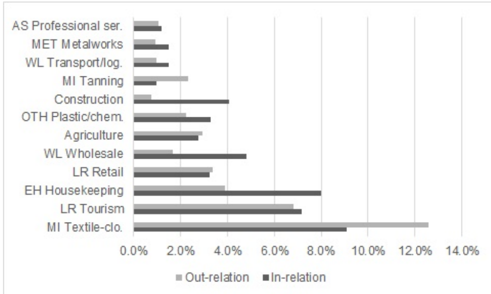
(a) MI Textile



(b) MI Food



(c) MI Woodwork



(d) MI Footwear

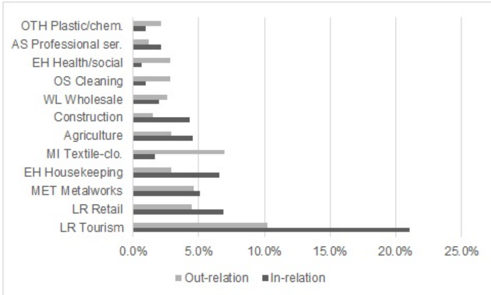
Figure 2. Top 12 in- and out-relatedness of MI sub-industries.

to all the other sectors; note that, as before, mobility refers to flows weighted by size before they are normalised over overall mobility and given as percentages. the Textile industry has the highest average mobility of about 25%; it is followed by Food (15%), Wood-Furniture (10%) and Footwear and Tanning; while Textile and Wood have more in-bound than out-bound mobility, Food has definitely more outbounds mobility. Figures 2a–l show detailed in- and out-relatedness of each of the 11 MI sub-industries; only the top 12 related sub-industries are reported and within sub-industry movements are excluded.

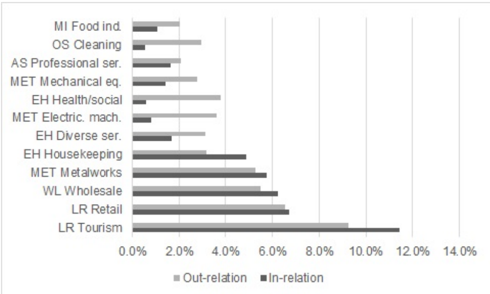
MI Textile is primarily related to Housekeeping, Tourism and Retail as reported in Figure 2a. In-relatedness for Housekeeping is much higher than its out-relatedness. It appears that workers move from housekeeping to textile and then to tourism. In the top 12 related industries, Textile is related to just one another MI, namely, MI Footwear. Food relatedness is mainly to Tourism. Moreover, it has high in-relatedness to Agriculture and out-relatedness to Retail reflecting movements along the product value-chain. Surprisingly, MI Woodwork is also primarily related to Tourism and less surprisingly, it is well-related to Metalworks and Construction. MI Footwear sources primarily from Textile followed by Housekeeping (as shown, they are themselves well-related) and Tourism. Moreover, its workers primarily join these industries.

The Construction industry is a major source of labour for MI Woodwork, Marble and Ceramics. The Tourism industry is a major source of labour for most MI sub-industries, however, MI Textile and MI Tanning recruit mainly from Housekeeping sector. In general, workers leave MI mainly to join the Tourism industry. However, the main target industries for Footwear and Tanning is Textile, for Marble it is Agriculture and for MI Ceramics it is Retail and Wholesale. The disaggregated figures reveal that in and out relations are not symmetrical.

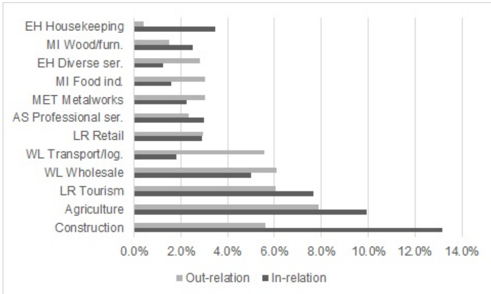
(e) MI Tanning



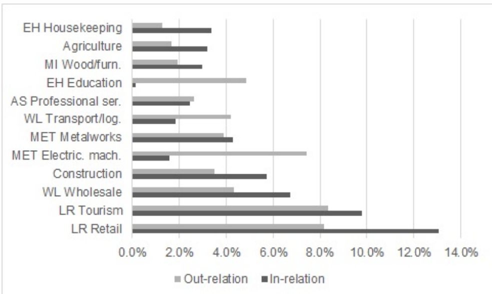
(f) MI Eyewear



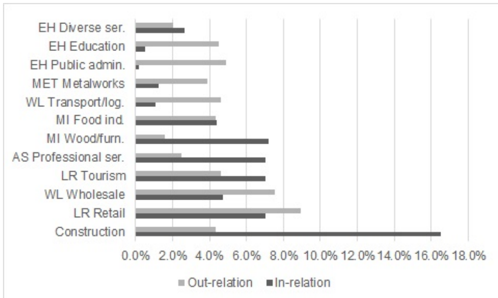
(g) MI Jewellery



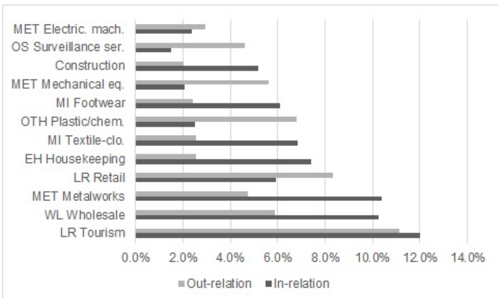
(h) MI Marble



(i) MI Glass



(j) MI Ceramics



(k) MI Other

Figure 2. Top 12 in- and out-relatedness of MI sub-industries.

4. Labour flow networks

4.1. *Some stylised facts about labour flow networks*

Table 6 shows the correlation matrix of a number of key network statistics and firm size (total employment). There is a high positive correlation between in- and out-degrees of 0.88 and in- and out-flows of 0.86 which can be interpreted as a fair amount of reciprocity in connections. Neighbourhood connectivity, which measures the average number of connections a node's neighbour has, correlates negatively with all degree centrality measures except clustering coefficient. This suggests that highly connected firms tend to link with less connected firms and vice versa, a stylised fact discussed below. The length of the shortest path from one node to another is a measure of the efficiency of information or knowledge flows. The average of this measure over all pairs of nodes do not correlate strongly with other measures. The correlations between firm size, measured by total employment, and degree centrality measures are positive but weak suggesting that not all large firms are those with more connections.

Table 6. Correlation matrix of network statistics

	1	2	3	4	5	6	7	8	9	10	11
1. In-degree	1										
2. In-flows	0.96	1									
3. Out-degree	0.88	0.85	1								
4. Out-flows	0.86	0.86	0.96	1							
5. Total degree	0.97	0.94	0.97	0.94	1						
6. Total flows	0.94	0.97	0.94	0.96	0.97	1					
7. Neighborhood connectivity	-0.02	-0.02	-0.03	-0.03	-0.03	-0.03	1				
8. Average shortest path length	0.03	0.04	0.17	0.14	0.10	0.10	0.01	1			
9. Betweenness centrality	0.01	0.01	0.00	0.00	0.01	0.01	-0.03	-0.06	1		
10. Clustering coefficient	0.03	0.04	0.03	0.03	0.03	0.04	0.11	0.08	-0.01	1	
11. Average employment	0.41	0.38	0.38	0.36	0.41	0.38	0.02	0.03	0.00	0.01	1

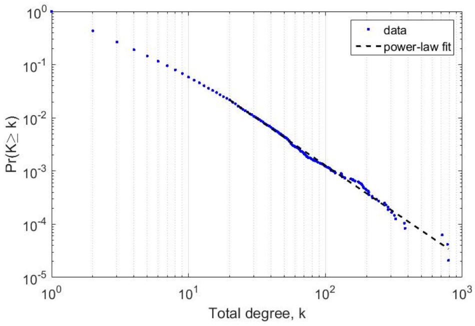
4.1.1. Long-tailed distributions

The degree distribution of a network provides insights into the structure of its total connections which can be decomposed into in and out connections.

The tendency of LFN to have long-tailed distributions has been reported in previous studies, namely, Gianelle (2014) and Guerrero and Axtell (2013) and extensively in other networks studies (Barabási and others, 2009). This property of the network suggests that firms with high degrees tend to be more frequent than if the data were normally distributed. That is to say, many firms are structurally important in the network as they both supply mobile workers to other firms and attract many workers to their premises. Maximum likelihood estimation is used to fit a power-law distribution of the form $p(k) \sim \beta k^{\alpha}$ where α is the scaling exponent and k_{min} is the threshold at which the power-law behaviour sets in. Indeed, a power-law with $\alpha = 2.74$ and $k_{min} = 20$ is a good fit[6] for the total degree distribution of the MI LFN. This feature of the network indicates the presence of hubs, i.e., nodes with many connections.

When the in- and out-degree distributions are plotted separately, only the in-degree distribution satisfies a power-law using maximum-likelihood estimations. This means that there are a few firms that hire a lot more than under "normal" standard. The same cannot be said for firms that fire. It should be noted, however, that the use of the less rigorous least-squares method to fit a power-law shows a high correlation between the empirical data and fitted line for both in- and out-degrees. The presence of hubs

[6] See Clauset et al. (2009) for methodological details

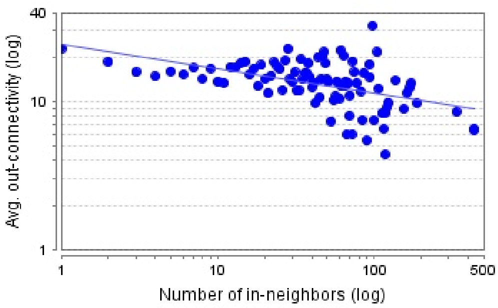


(a) Total-degree distribution (complementary cumulative distribution function). *p-value=0.427*

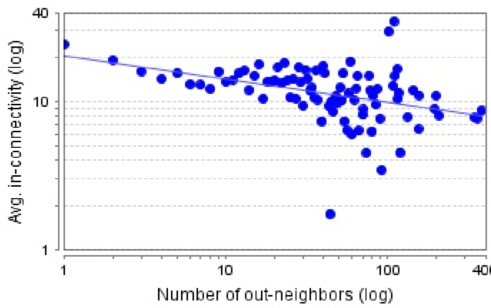
implies that connections are concentrated; indeed, the top 20 percent of firms make up 66 per cent of all flows.

4.1.2. Disassortativeness

Do workers move between firms that are similar in terms of their connections? The concept of neighbourhood connectivity is useful to answer this question. Most social networks tend to be assortative in nature, that is, an agent will usually interact with another agent that is roughly as popular as itself, i.e, has a similar number of interactions. Figure 3a shows the out-neighbourhood connectivity distribution of all source firms of i and Figure 3b shows the in-neighbourhood connectivity distribution of all target firms of i. A power-law is fitted to the logarithmised data using least-squares method. The negative coefficients for both plots evidence some disassortativity of the MI LFN where workers tend to move between firms that have opposing number of connections. Previously, Guerrero and Axtell (2013) studying the Finnish labour market also finds disassortativity especially for firms with more than 34 connections. Given the weak but positive correlation between degree and size, such a disassortative relationship vaguely suggests that workers move from relatively large to small firms and vice-versa.

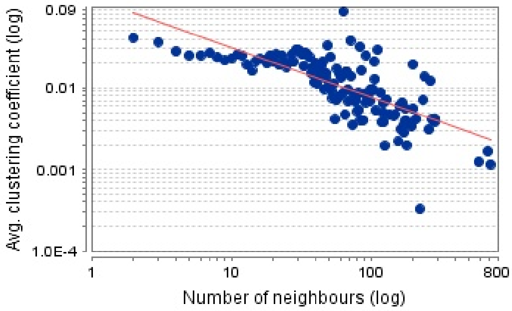


(b) In-neighbours connectivity *a= 24.09 b=-0.162 corr=0.415 R-sq=0.238.*



(c) Out-neighbours connectivity *a= 20.19 b=-0.156 corr=0.384 R-sq=0.163.*

Figure 3. In- and out-neighbourhood connectivity distributions of the MI network.



(a) Average clustering coefficient distribution.

Figure 4. The relationship between average clustering coefficient and number of neighbours.

4.1.3. Hierarchical structure

In directed networks, the clustering coefficient of node i with degree k is $\frac{e_i}{k_i(k_{i-1})}$ where e_i is the number of connected pairs between the neighbours of i. The average clustering coefficient is its average for all nodes i with degree k for $k = 2, \ldots$. Clustering coefficient is a popular measure of the structural importance of a node in a network. As regards LFN, it provides insights into the extent to which a firm facilitates labour reallocation. Figure 4 shows a clear negative relation between the average clustering coefficient and degree of firms. Just as in Guerrero and Axtell (2013), this relation falls through a power-law relation with an R-squared of 0.5. Following Ravasz (2003), such a distribution can be said to have a hierarchical network organisation with embedded modularity. There is high level of activity at many organisational levels. Firms with few links, in other words, smaller firms, are highly integrated clusters; these small clusters combine to form larger but less connected clusters (Barabasi, 2009). Labour associated with firms positioned up in the hierarchy have better access to other firms and are, thus, more employable. See the following section for cluster analysis.

4.1.4. Small-world network

As shown in Table 7, the mean number of connections (both incoming and outgoing) of the MI network is 3 with a standard deviation of 10 and a maximum of 792. The average shortest path of 3.7 is much smaller than the total number of nodes in the network, which implies that each firm is connected to any other by less than 4 worker flows indicating fairly easy reachability of firms to workers and vice-versa. The MI network is thus, permeable, a property that is useful to ensure the absorption of cyclical shocks (Gianelle, 2014). To better assess the relevance of these statistics, they are compared with those of an Erdòs-Renyi random-model. A recently developed randomisation procedure is used to produce the random model; it allows the number of nodes and the degree sequences of the original network to be maintained while the links are reshuffled randomly (Maslov and Sneppen, 2002). The MI network is more clustered than its random counterpart and its average shortest path is roughly similar. These provide evidence that the structure of labour flows is not the result of a random process but there is some deliberate organisation occurring. These two properties of the network, segregation and integration, make it a small-world network (Watts and Strogatz, 1998).

Table 7. Actual network vs random model vs MNEs

	Whole network: 47706 nodes				Random network	MNEs: 227 nodes			
Variable	***Mean***	***S.D.***	***Min***	***Max***	***Mean***	***Mean***	***S.D.***	***Min***	***Max***
Links	3.31	10.5	1	792	**3.31**	12.87	26.2	1	186
Indegree	1.65	5.6	0	438	**1.65**	6.46	13.7	0	84
Outdegree	1.65	5.3	0	377	**1.65**	6.41	13.4	0	119
Neighborhood conn.	39.41	95.8	1	710	**37.30**	44.94	78.4	1	710
Avg shortest path	3.67	3.2	0	15.6	**3.23**	4.70	2.4	0.0	10.0
Clustering coef.	0.01	0.1	0	1	**0.001**	0.02	0.1	0	0.83
Betweenness central.	0.00	0.03	0	1	**0.00**	0.00	0.00	0	0.005
Closeness central.	0.22	0.30	0	1	**0.23**	0.18	0.18	0	1
Eccentricity	8.63	7.7	0	25	**6.77**	12.05	6.1	0	19
Employees	21.5	135.8		12074		114.3	152	0	1078

4.2. *Are MNEs different from the rest of firms?*

It is acknowledged in the literature that working in MNEs provides exposure to rich knowledge and information that differs from the internal context. The introduction of external knowledge prevents inertia or lock-in that often happens within a localised learning boundary. Workers accumulate knowledge while they are involved with an MNE and they consequently transmit it to local hiring firms. For instance, Ebersberger et al. (2011) uses Finnish labour mobility data for the period 1995 to 2004 and shows that firms that hire from MNEs experience an increase in innovation activities and success whereas firms that hire from uninationals experience a decrease in innovation activities and success. Moreover, high labour mobility has a stronger positive impact on innovation activities when the hiring firm is uninational firms than when it is an MNE. The paper, thus, argues that higher mobility enlarge the competence base of national firms.

When compared to the whole set of firms, MNEs have more connections, about 13 links on average compared to just over 3 links for the average firm. Independent samples t-test with unequal variances confirms the significance of the difference, $t = -5.53$. Their neighbours are as well-connected as the rest of firms (since there is no significant difference for these measures). This finding suggests one or a combination of the following: first, MNEs select to locate near integrated groups of firms (to benefit from an existing pool of labour); second, MNEs create an environment that facilitates the integration of firms through labour movements. The cluster analysis in Section 4.4 further investigates these findings.

While the average clustering coefficient of the network is higher than that of the random network, that for MNEs is highest and this result reinforces the previous finding. MNEs have longer average shortest paths compared to all other firms; this indicates that workers cannot reach them easily due to the fact they are smaller in numbers but also probably because they require and select into specialised skills. MNEs high eccentricity score, which measures the maximum shortest path length, corroborates the reasoning that much effort is needed for workers to access multinationals. On average, MNEs are larger than national firms as indicated by their much higher average employment figures, 114 against 21.

4.3. *Disaggregated network statistics by sub-sectors*

Table 8 reports the mean network statistics of each sub-sectors. The top and bottom 5 statistics are marked as *hi* and *lo* respectively. The Tanning, Eyewear, Food, Glass and Footwear MI industries are those with highest mean degrees, in, out and total. As MI industries are the common denominator, it is expected that they have the highest number of the links. However, Public administration is present amongst the top five sectors

Table 8. Various network statistics by sub-sectors

	Total degree	Indegree	Outdegree	Neighb.	Avg. sh. path	Between.	Closeness	Clustering	Avg. employ.
Agriculture	1.88	1.11	0.76	57.9	3.08	0.1%	0.15	0.02	5.30 lo
AS Culture/publish	2.37	1.21	1.16	57.5	3.36	0.0%	0.13	0.00 lo	23.2
AS IT services	1.46	0.74	0.73	54.4	3.16	0.0%	0.17	0.00	18.3
AS Professional	1.69	0.95	0.74	61.7	3.08	0.0%	0.13	0.01	14.9
AS R&D	1.36	0.59	0.77	68.1 hi	5.34 hi	0.0%	0.12 lo	0.00 lo	44.4
AS Telecommu.	1.58	0.77	0.81	59.3	3.52	0.0%	0.13	0.01	96.3 hi
Construction	1.29 lo	0.53	0.76	65.4 hi	3.81	0.0%	0.17	0.01	9.2
EH Diverse ser.	1.90	1.14	0.76	45.0	3.02	0.0%	0.14	0.01	17.1
EH Education	2.43	1.87	0.56	59.1	2.40 lo	0.0%	0.10 lo	0.02	63.2 hi
EH Health/social	2.63	1.86	0.77	51.6	2.94 lo	0.0%	0.14	0.01	99.2 hi
EH Housekeeping	1.13 lo	0.61	0.52	44.1	3.06	0.0%	0.13	0.01	1.40 lo
EH Public admin.	3.82	2.91 hi	0.91	50.2	2.95 lo	0.0%	0.12	0.02	48.6
EH Repairs/renta	1.33 lo	0.65	0.68	50.9	3.47	0.1%	0.16	0.01	6.00 lo
FN Credit	1.99	0.85	1.14	61.5	3.87	0.0%	0.16	0.02	246 hi
FN Finance/ins.	1.36	0.84	0.51	67.8 hi	2.78 lo	0.0%	0.10 lo	0.00	28.0
LR Retail	2.05	1.06	0.98	45.8	3.29	0.1%	0.17	0.01	20.8
LR Tourism	1.62	0.88	0.74	53.4	3.30	0.0%	0.15	0.01	10.2
MET Electric. ma	2.97	1.43	1.54	59.0	4.22	0.0%	0.16	0.03 hi	41.4
MET Mechanical e	2.30	1.21	1.09	63.0	3.55	0.0%	0.15	0.02	34.9
MET Metalworks	2.16	1.12	1.03	58.5	3.70	0.0%	0.16	0.02	22.5
MET Transport ve	2.58	1.27	1.31	50.7	4.01	0.0%	0.17	0.01	45.1
MI Ceramics	3.69	1.64	2.05	7.4 lo	3.68	0.5%	0.39 hi	0.00 lo	12.3
MI Eyewear	10.7 hi	5.27 hi	5.47 hi	24.0	4.24	0.2%	0.30	0.03	38.9
MI Food ind.	7.55 hi	3.79 hi	3.77 hi	10.4 lo	3.79	1.2% hi	0.36 hi	0.01	10.2
MI Footwear	6.04 hi	2.88 hi	3.16 hi	14.3	4.79 hi	0.4%	0.32	0.02	11.2
MI Glass	6.20 hi	2.80	3.40 hi	10.6	3.97	1.2% hi	0.32	0.00	15.3
MI Jewellery	3.78	1.64	2.14	11.2	3.89	0.5%	0.34	0.01	6.6 lo
MI Marble	3.56	1.64	1.92	10.1 lo	3.79	0.8% hi	0.36 hi	0.01	6.9 lo
MI Other m.Italy	5.17	2.53	2.65	9.3 lo	3.60	0.8% hi	0.39 hi	0.00	7.7
MI Tanning	11.3 hi	5.92 hi	5.38 hi	25.4	4.72 hi	0.5%	0.25	0.05 hi	13.9
MI Textile-clo.	4.87	2.19	2.68	10.2 lo	4.63 hi	0.3%	0.33	0.02	7.8
MI Wood/furn.	4.61	1.93	2.68	12.4	3.98	0.7% hi	0.35 hi	0.01	9.7
Mining-quarry.	1.21 lo	0.50	0.71	68.7 hi	4.39 hi	0.0%	0.11 lo	0.00 lo	23.9
OS Cleaning	3.59	2.23	1.36	60.3	3.22	0.0%	0.15	0.02	45.5
OS Real estate	1.52	0.92	0.60	50.2	2.73 lo	0.0%	0.13	0.01	10.8
OS Rental ser.	1.35 lo	0.65	0.69	60.4	3.43	0.0%	0.11 lo	0.00 lo	7.4
OS Surveillance	2.75	1.50	1.25	55.5	3.75	0.0%	0.16	0.01	25.6
OTH Building mat	2.11	0.97	1.14	53.6	3.90	0.0%	0.19	0.03 hi	27.2
OTH Other ind.	2.57	1.21	1.36	52.6	4.11	0.0%	0.19	0.02	14.6
OTH Paper-printi	2.49	1.24	1.25	74.4 hi	3.83	0.0%	0.18	0.02	25.5
OTH Pharmaceut.	2.96	1.73	1.24	64.1	3.58	0.0%	0.17	0.03 hi	59.4 hi
OTH Plastic/chem	3.41	1.82	1.59	57.4	3.93	0.0%	0.15	0.03 hi	30.2
Utilities	2.22	1.29	0.93	47.5	3.19	0.0%	0.13	0.02	58.7
WL Transport/log	2.63	1.40	1.23	57.8	3.66	0.1%	0.15	0.02	35.7
WL Wholesale	1.98	1.01	0.96	45.0	3.43	0.0%	0.16	0.01	15.2

hi and *lo* are the top and bottom 5 statistics respectively.

with highest mean in-degrees which highlights its major role in recruiting workers from MI. Industries whose neighbourhood have the highest average number of connections are Paper-printing, Mining-quarrying, Research-development, Finance-insurance and Construction. Note they are all non-MI industries with low degrees as expected from the disassortativity results explained above. They appear to be supporting industries necessary for MI, for instance, R&D for Textile-clothing and Construction for Ceramics industries.

Reachability of a sector can be inferred from the average number of steps it takes to connect it to other firms, that is, sectors with low average shortest path length (Av. sh. path) are more accessible than those with long paths. The Education sector is the most accessible to and from all the other firms in the network, followed by Real Estate, Finance-insurance, Health-social services and Public administration. Education, Health-social services and Public administration are large employers and this may explain their accessibility. The reachability of the Finance-insurance sector is due to the high demand for the specific skills of its workers. R&D, Footwear and Tanning have the longest shortest path lengths and they are known to require highly specialised labour and, hence, have mostly intra-sectoral mobility. Tanning also has one of the highest mean clustering coefficient. This makes it a well-integrated industry where workers move easily between similar firms that produce highly mobile workers. Pharmaceuticals, Electrical machines, Building materials and Plastic-chemical are other highly clustered industries. In these industries too, specific skills and experience are usually required which favours within sector flows.

MI industries lead in betweenness centralities given that by definition they are the sectors under study and all workers necessarily go through them. They are on the path of many mobile workers. Food industry has the highest mean betweenness centrality followed by Glass, Marble industries and Other-MI. Interestingly, they also have high closeness centrality, thus, reachable. The largest industries in terms of employment are Credit companies, Health-social services, Telecommunications, Educational sector and Pharmaceuticals. The smallest industries are Housekeeping, Agriculture, Repairs-rental services, MI Jewellery and MI Marble. Note that despite MI Marble being a small industry, it does play an important role in bridging other firms as evidence by its high betweenness centrality.

4.4. *Cluster identification and visualisation*

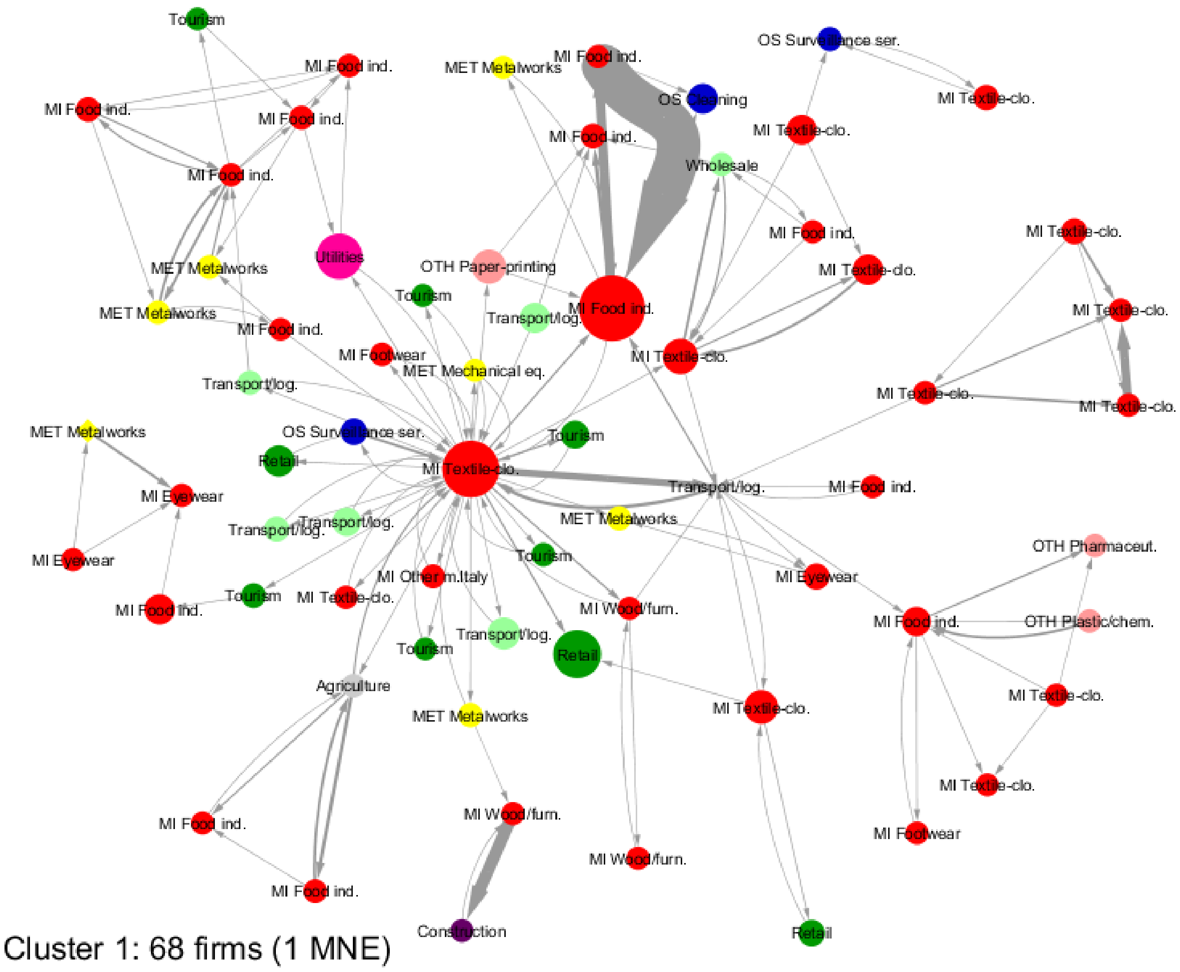


Figure 5. Cluster 1

Previous results provide good insights into the structural properties of the MI labour flows and the extent of clustering in the network. In order to better assess the validity of these results, a sophisticated algorithm[7] that can detect highly interconnected regions in a network is used to identify clusters of firms with intense labour movements.

It operates through a 3-stage process, briefly described here. First, all nodes are assigned a score according to their local network density. Second, starting with the highest weighted node, other nodes are added recursively if they satisfy a given threshold; nodes of less than 2 degrees are not scored. Third, filters are applied to improve the quality of the clusters. In this analysis, clusters that are not maximally interconnected sub-clusters of at least 3 degrees are dropped; nodes that only have a single connection to the cluster are dropped, and; the algorithm is set to search for nodes as far as 100 steps away from the seed node. Given these parameters and after applying the filters described above, the algorithm identifies 32 clusters in the MI LFN. The first 5 largest clusters in terms of their number of nodes are illustrated. The size of each node is proportional to its size, that is, total employment and the size of an arrow is proportional to the flow of workers. MI firms are coloured red and each node's label shows its sub-industry. Leisure-retail are coloured green; Metalworks-mechanics are yellow; Logistics-wholesale are light green among others. Multinationals are distinguished by their diamond shape.

4.4.1. Cluster 1

Cluster 1 is made up of 68 firms with 135 links and 267 flows. It is mainly composed of firms operating in Food industry and Textile-clothing. Nonetheless, it is a very diversified cluster in terms sectoral composition with 48% of non-MI firms ranging from agriculture to utilities. It has one MNE operating in the Metalwork sector. Disassortativity is evident with a number of connections between highly-connected and less-connected firms. This cluster also shows the closeness of Food to other industries and its bridging role as the statistics in Table 8 show. It also shows how the Textile-clothing industry has very low neighbourhood connectivity. The strong presence of Transport-Logistic, Tourism and Metalwork firms confirms that there exists a certain degree of relatedness between these industries. Textile-clothing sector and Wood-furniture industry have lost considerable workers, 24, to other industries while Construction has gained 13 workers. Firms that are only recruiting are Cleaning and Pharmaceutical. 11% and 21% of mobile workers are high-skilled and medium-skilled respectively. See Table A in the Appendix for statistics on skills, contracts and education for the clusters. Mobile workers are primarily on fixed-term, 43%, and staff-lease, 36% contract; Most of them, 54%, have diploma education and 33% have compulsory education.

4.4.2. Cluster 2

Cluster 2 has 46 firms with 130 links and 218 flows and 4 MNEs. Woodwork-furniture has the highest number of firms and highest flows followed by the Food industry. Woodwork, Footwear and Eyewear exhibit more intra-industry mobility. Just as in cluster 1, the closeness of Food to services industry is evident. These sectors show strong integration with other non-MI sectors namely the Tourism sector. It is interesting to note the sub-cluster made up of 3 MNEs operating in the Footwear industry; this suggests that MNEs share a common labour pool with specialised skills. However, the single MNE operating in the Food industry connects to many different sectors, namely, Textile, Tourism, Paper-printing. Transport-logistic is a major recruiter and workers come from Woodwork-furniture and Footwear sector. There is a clear indication of

[7] The algorithm MCODE is used here. It is used mainly in the natural sciences to detect molecular complexes.

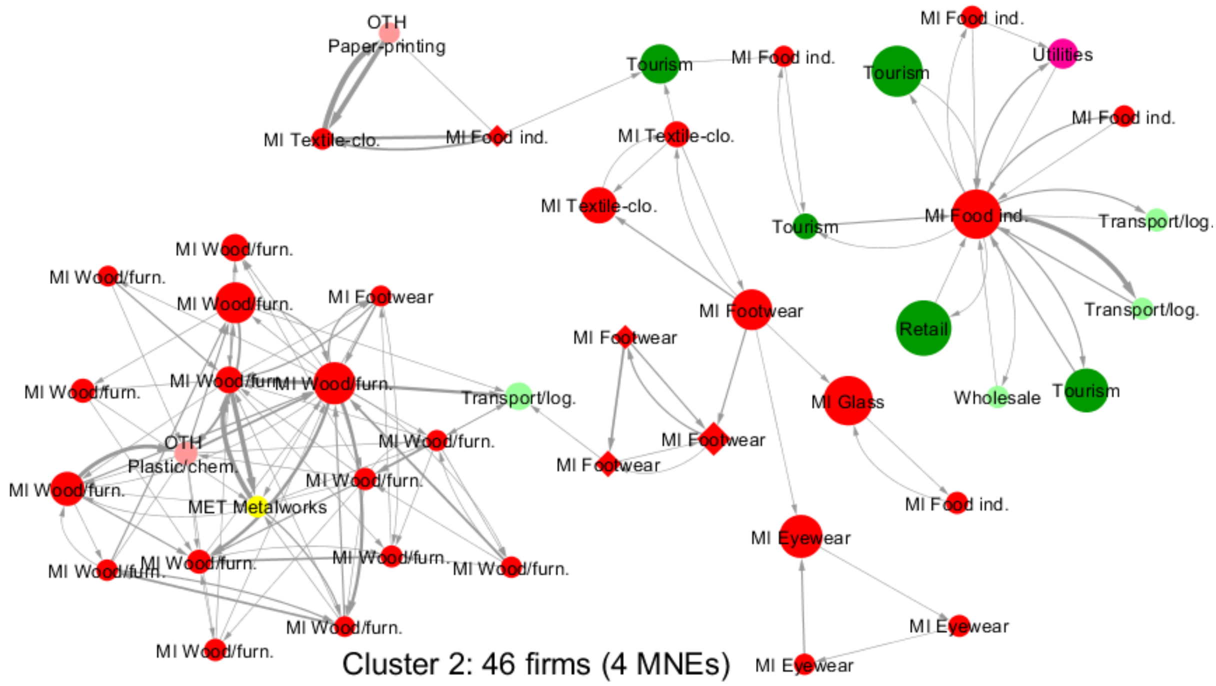


Figure 6. Cluster 2

declining employment in MI and increasing employment in services such as Transport-logistics and other industries. An impressive 25% of mobile workers are highly skilled; 71% are on staff-lease and 11% on permanent contract (See Table A).

4.4.3. Cluster 3

The third cluster has 113 links and 243 flows. It is a specialised cluster with 39 firms out of which 33 belong to the Tanning industry; this corroborates with Tanning's high clustering coefficient as seen in Table 8. The cluster is dominated by intra-industry flows which is reflected in Tanning's long average shortest paths. Indeed, no MNEs are present. The presence of firms from Transport-logistics, wholesale and agriculture reflects movements along the industry's supply chain. However, the Transport-Logistics sector together with the Health-Social services sector are growing while the Tanning industry is contracting. Note that there are only 4% of high-qualified mobile workers, much less than in previous clusters that exhibit more inter-sectoral flows. Moreover, 84% have only compulsory education and 10% have diploma. Data on provincial location suggest that the tanning industry seems to classify as an industrial district in the classical sense; it is geographically localised with all firms in the Vicenza province (provincial data are not reported here).

4.4.4. Cluster 4

Cluster 4 is similar to cluster 3 in its structure. It is highly clustered and localised in the Vicenza province and it has no MNE presence. It consists of 35 firms, 30 of which belongs to the Tanning industry; 324 out of 353 flows occur within the Tanning industry. Still, it has intense intra-sectoral flows involving the Wholesale and the Me-

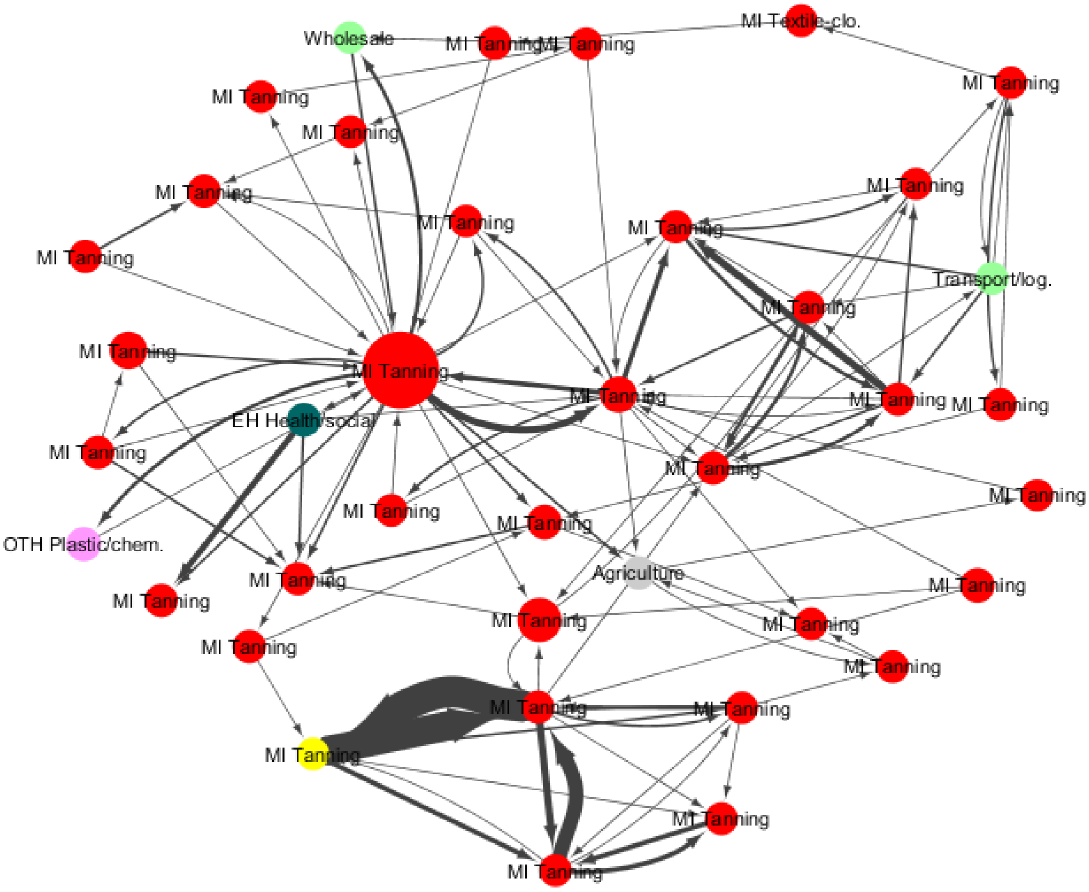


Figure 7. Cluster 3

chanical equipment industries. It also resembles cluster 3 in that its mobile workers are mostly low-skilled and are on staff-lease contracts. Nevertheless, it has very high average number of flows and a high clustering coefficient just as in the whole network, see Table 8.

4.4.5. Cluster 5

Cluster 5 has 33 firms, 52 links and 99 flows. The inter-sectoral nature of the cluster is high. Most flows revolve around a relatively large firm operating in the Food industry that recruits 27 workers and fires from 22; its bridging role reflects the high betweenness centrality of Food industry reported in Table 8. This firm has a direct link to just one firm operating in the same sector while all other links are to firms from sectors ranging from Agriculture to Public administration–evidence of its closeness to other firms. Interestingly, 32% of mobile workers are non-qualified while only 2% are highly qualified. However, it has more mobile workers with diploma compared to the tanning clusters. It has more mobile workers on a permanent contract compared to other clusters. From cluster 1 and 5, it can be said that Food industry relies on a wide range of skills and its flows tend to be inter-sectoral.

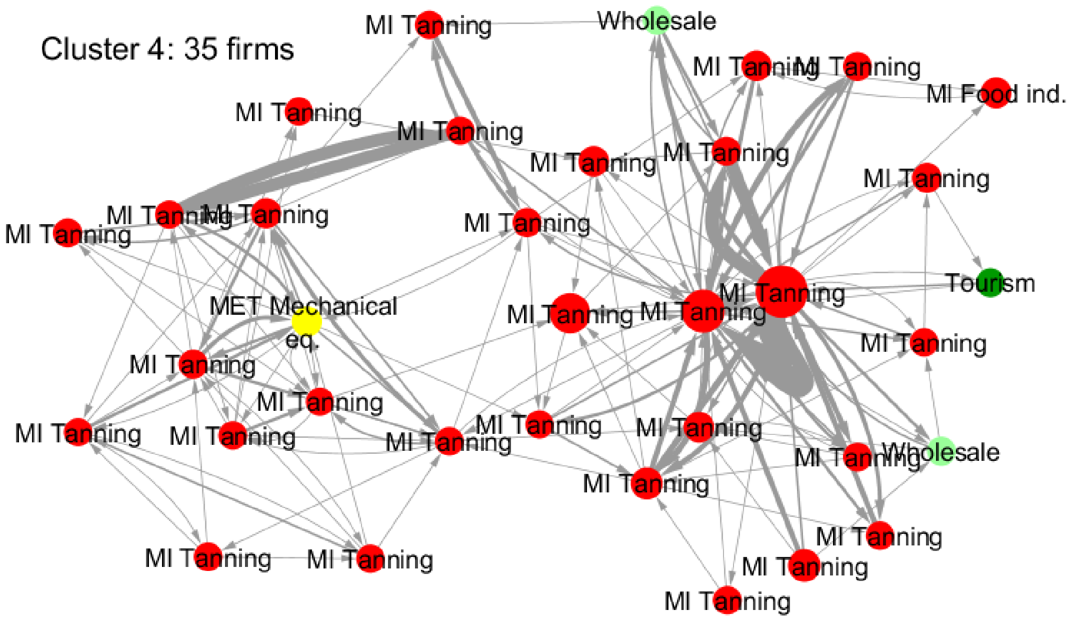


Figure 8. Cluster 4

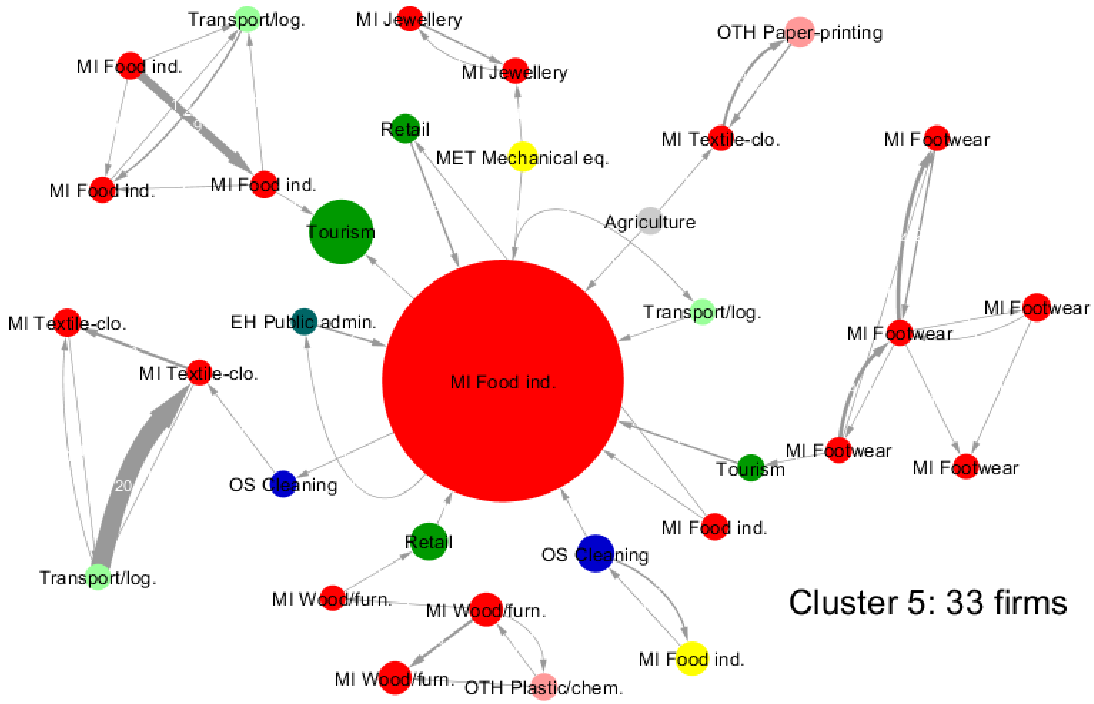


Figure 9. Cluster 5

4.4.6. Cluster 6

Cluster 6 has 32 firms, 50 links and 73 flows. One third of firms, 10, are from the Footwear industry and their intra-industry links is evident; this result again explain their long average shortest path length. Nevertheless, there is a strategic link to a

Wholesale firm. There are 3 MNEs operating in the MI sector: 1 in Footwear, 1 in Tanning and 1 in Food industry. They tend to be close to each other as in other clusters where they are present. Highly skilled mobile workers make up 8% of flows; 44% are on permanent work contract. The MI sector lost 6 workers while Retail and Transport-Logistics sector together gained 7 workers.

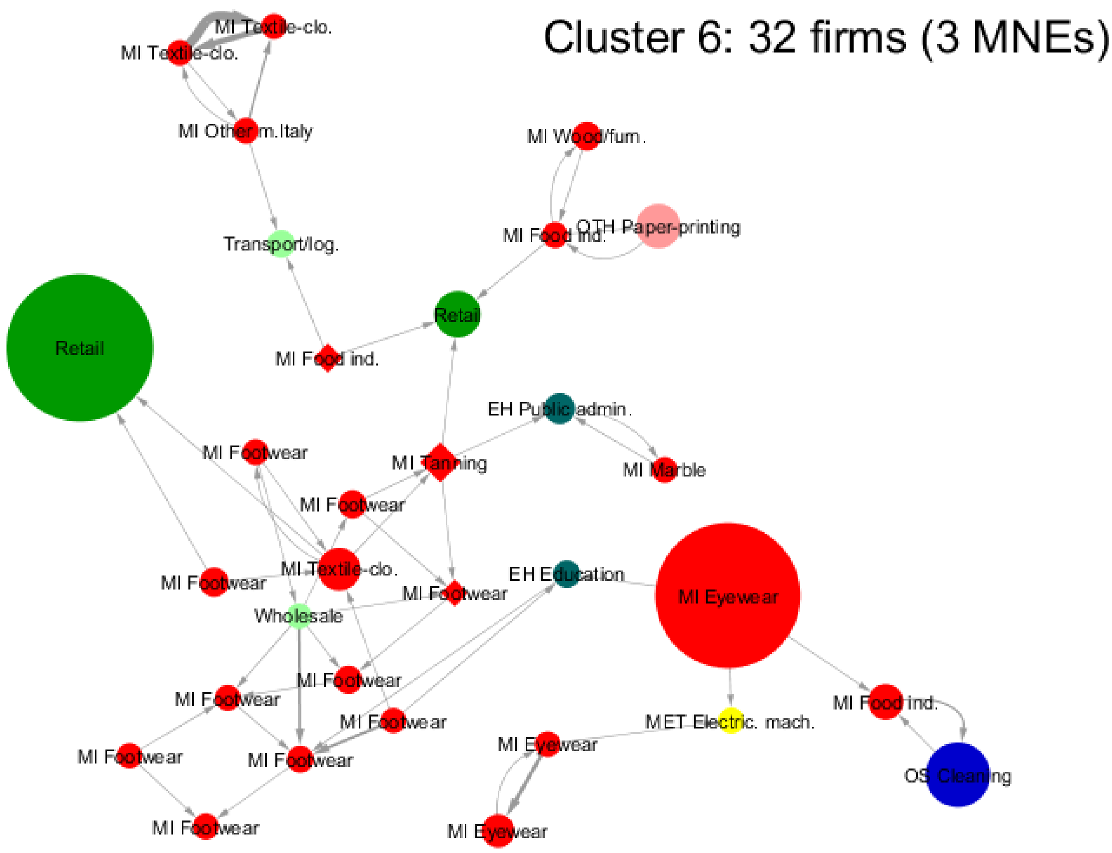


Figure 10. Cluster 6

4.4.7. *Cluster 7*

Cluster 7 shows the inter-sectoral nature of labour flows and its disassortativity. The high-clustering coefficient of Electrical machinery industry is highlighted in this cluster. It has 4 MNEs and 2 of them have considerable exchange of workers although one is from Food industry and the other from Electrical machinery sector. The cluster has 22% of high skilled and 15% of medium skilled mobile workers. An impressive 30% has degree education.

4.4.8. *Cluster 8*

The inter-industrial nature of labour flows is also observed in Cluster 8 with firms from Transport-Logistics, Textile-clothing, Tourism, Food industry and even Surveillance. Again, the closeness of the Food industry to other firms is striking. It is quite evident that the neighbours of the two food industry firms are poorly connected, a fact mea-

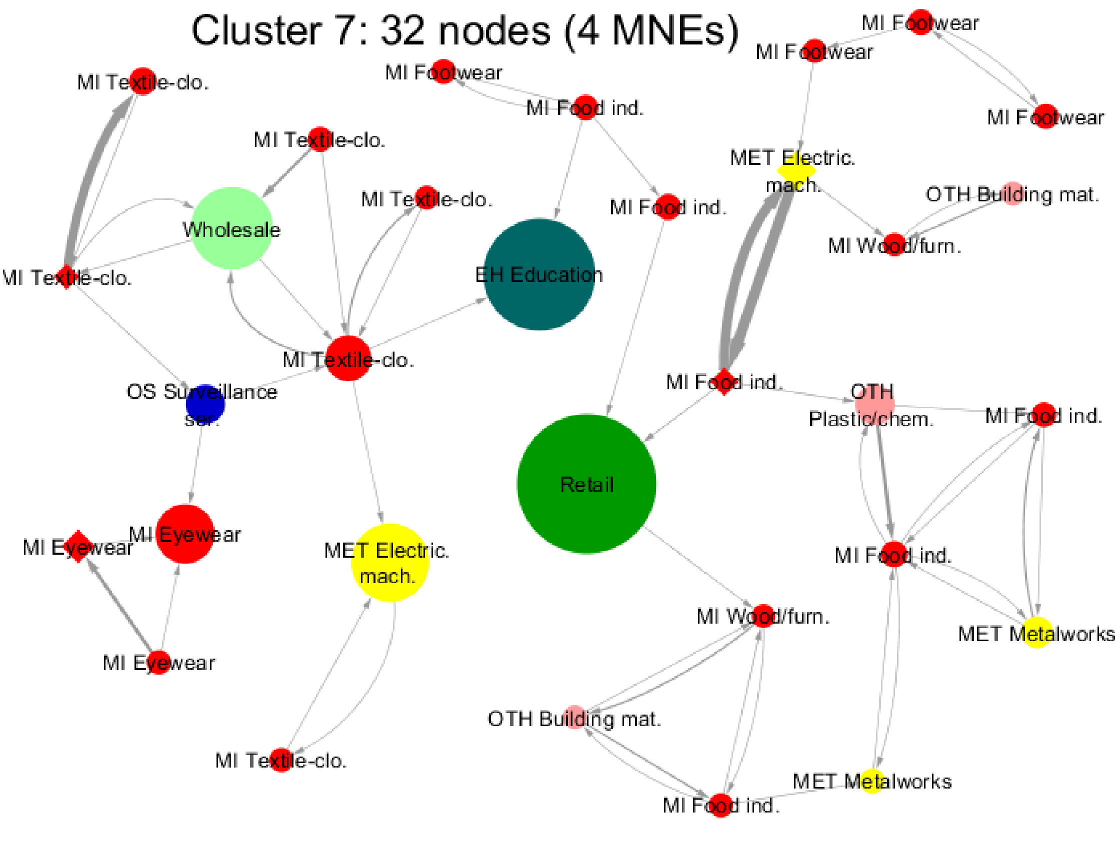


Figure 11. Cluster 7

sured by the neighbourhood connectivity statistic in Table 8. No MNE is present in this cluster. Only 1% of mobile workers are high-skilled and most of them have fixed-term contract and compulsory education.

4.4.9. Cluster 9

The intra-industrial nature of flows in the Tanning industry compared to the inter-industrial nature of the Food industry is manifest in Cluster 9. The retail firm plays a central role in bridging 3 sub-clusters. While the majority of mobile workers are low-skilled, 11% are high-skilled.

4.4.10. Cluster 10

Cluster 10 is made up of 16 Tanning firms. Tanning is the industry with the highest number of average connections, so its workers are highly mobile but they only move within industry. Indeed, the average number of connections in this cluster is 5.5. It also has one of the highest clustering coefficient as reported in Table 8. Note that only 87% of workers are low-skilled; this result corroborates with findings of Table 4 that low-skilled workers are also quite mobile intra-MI. In this cluster, mobile most mobile workers have compulsory education and none has degree education. This confirms results in Table 5 that those with low educational level are more mobile within industry.

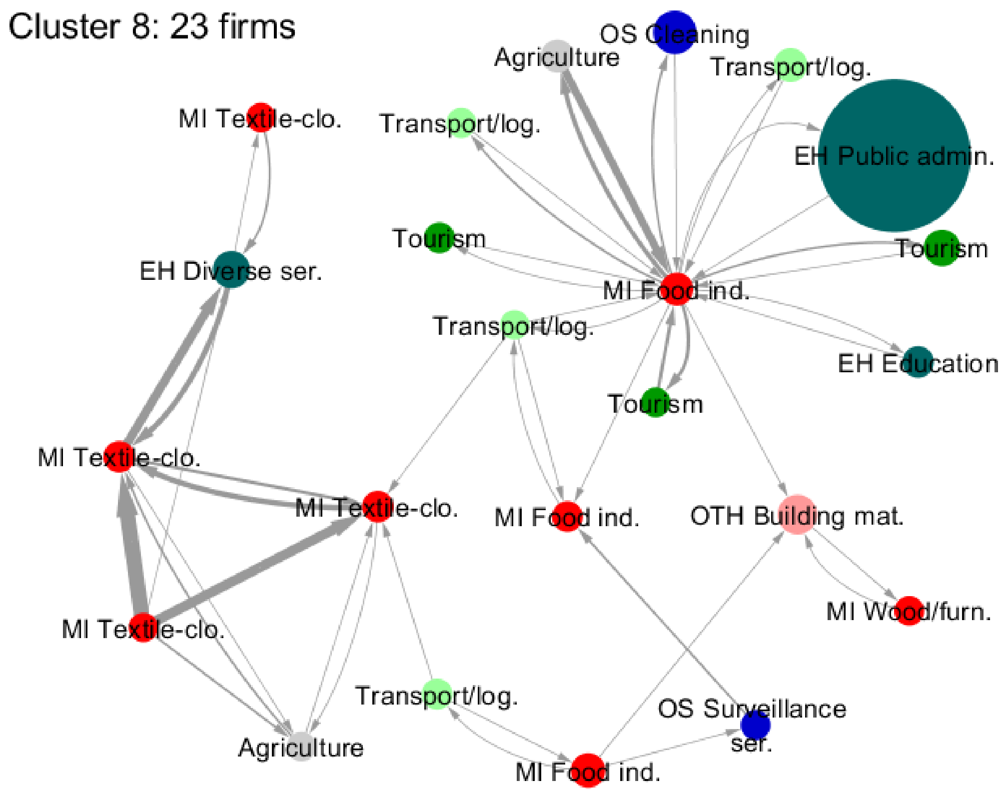


Figure 1

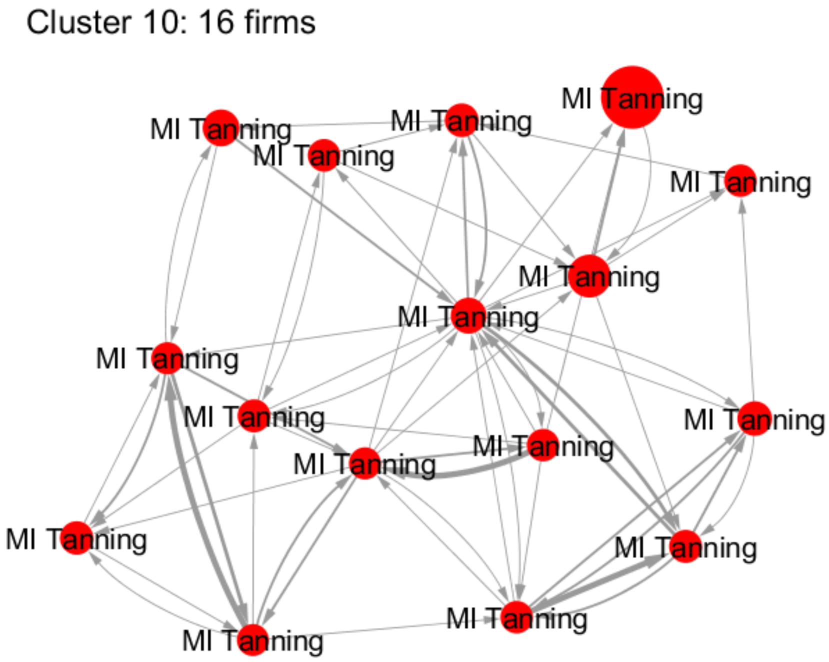


Figure 14. Cluster 10

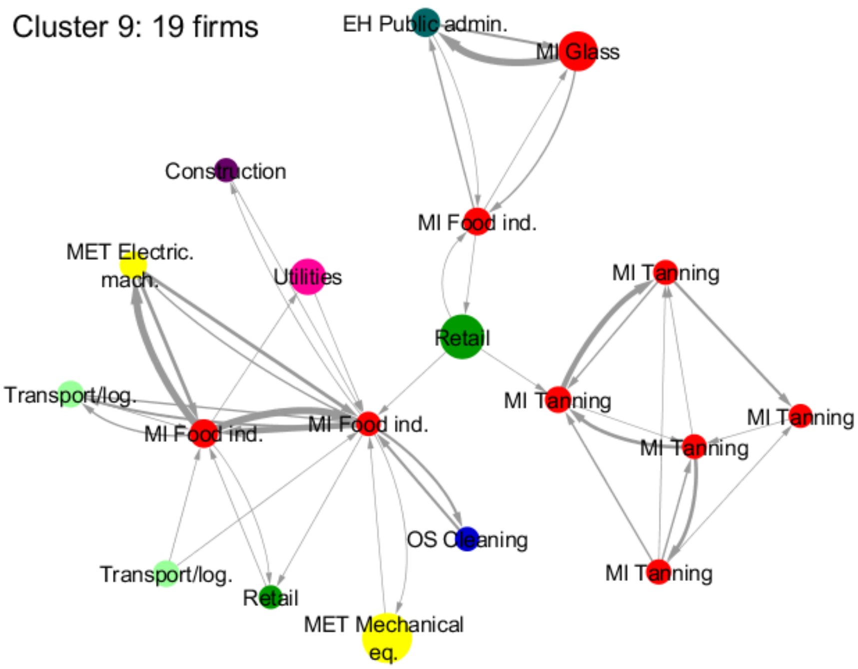


Figure 13. Cluster 9

4.4.11. Cluster 11

Cluster 11 is highly inter-sectoral and exhibits disassortativity. Real estate is one of the industries with very short average shortest path length and this is reflected in this cluster. The bridging role played by Food industry firms is also well-represented. The movement of workers along the value chain can be traced, such as, from agriculture to food and to tourism or retail firms. High-skilled workers make up 15% of the workforce and only 3% are on long-term work contracts.

4.4.12. Cluster 12

One-half of the 14 firms in cluster 12 are from Eyewear industry which is highly-clustered (but not as clustered as Tanning). Two MNEs are present and as in previous clusters, they are connected. A large percentage of workers are high-skilled (18%) but none have permanent work contracts.

4.4.13. Cluster 13

Most firms in Cluster 13 are from Textile-clothing and they are connected among themselves. However, they are connected to Housekeeping services and Plastic-chemicals industries. 99 percent of workers are low-skilled and 90 percent are on a permanent contract.

4.4.14. Cluster discussion

In this section, clusters of intense labour flows have been identified using a novel algorithm. Such an exercise allows the visualisation of results found in Section 3 and 4; in particular, the relatedness of sub-industries and the network statistics results can be pictured. Some of the main results are discussed below.

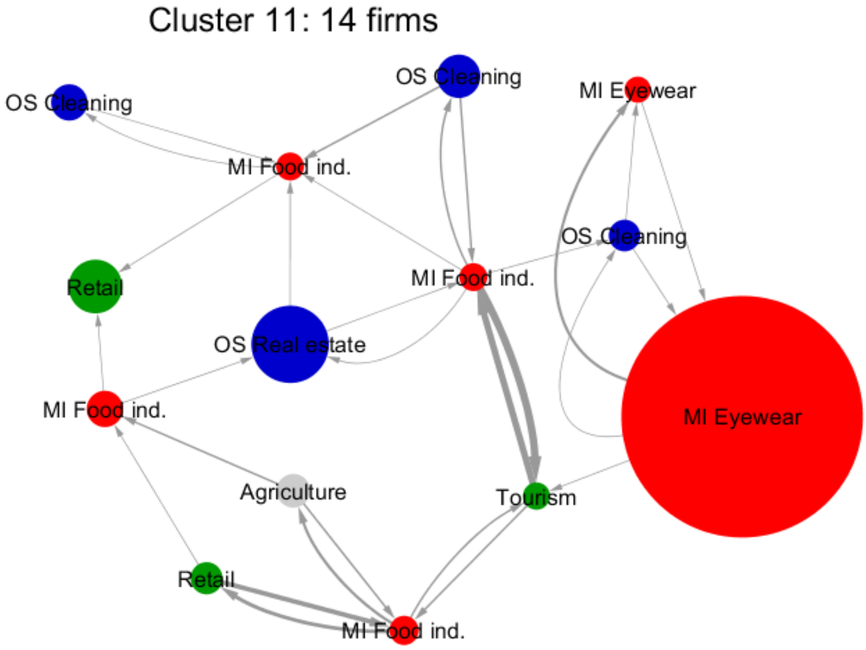


Figure 15. Cluster 11

First, it appears that some industries are inherently intra-sectoral while others are inter-sectoral in their exchange of labour. For instance, Tanning is highly intra-sectoral. It has many connections but has long average shortest path length: this means within-industry flows. Moreover, its mobile workforce is low-skilled and on staff-lease work contract. To a lesser extent, Woodwork and Footwear also have many intra-sectoral links; these industries, however, have more connections with other sectors up and down the value-chain.

Second, Food industry exhibits strong inter-sectoral flows; it connects with all other sub-sectors, even Mining-quarrying and Telecommunications. It plays a central role in all clusters where it is present as shown by its high betweenness centrality. It is very close to most services industries, in particular, tourism. In other words, workers from the Food industry are more employable than workers from Tanning when they seek employment in different industries.

Third, clusters that exhibit more inter-sectoral flows tend to have more higher skilled mobile workers compared to clusters composed of same industry firms. For example, the diversified cluster 7 has 37% compared to the homogeneous Tanning cluster 4 that has only 3% of mobile workers that are high-medium skilled.

Fourth, it also appears that clusters that include MNEs locate in inter-sectoral clusters and, from the third point above, in clusters that have more higher skilled mobile workers. Nevertheless, MNEs prefer to connect to each other.

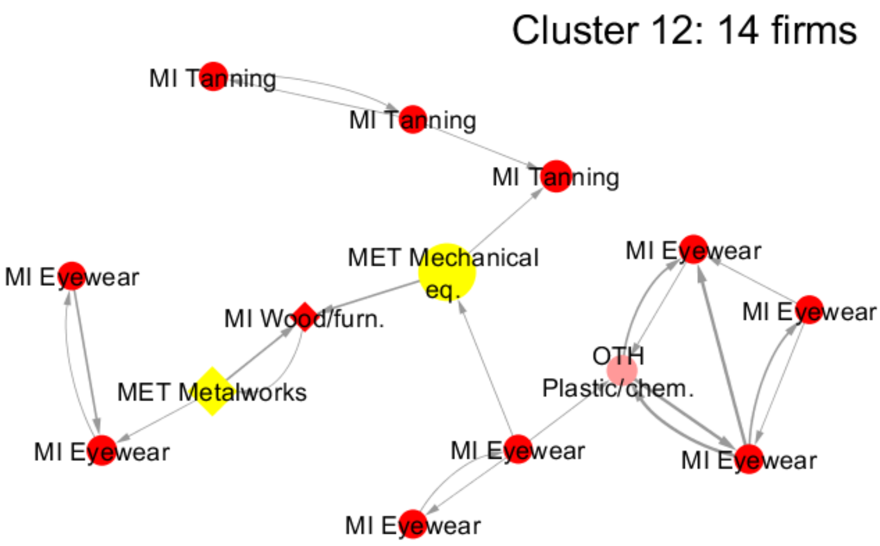


Figure 16. Cluster 12

5. Empirical analysis: Network statistics and performance

It is well-documented in the literature that acquiring knowledge from external sources benefits the firm (Poole, 2013). This happens because it prevents lock-in or inertia wherein firms tend to get entangle in a certain way of doing things, thus, preventing the expression of creativity and innovation (Boschma, 2005). It is suggested here that acquiring knowledge by hiring from many different firms should have a positive effect on firm performance. One could argue, however, that exit of workers may have mixed effects: on one hand, increased out-connectivity may signal a well-performing firm producing knowledgeable and, hence, versatile workers. On the other hand, it may signal poor performance that force workers to exit. However, in this paper, it is argued that labour churning inside a firm is simply a mechanism it uses to find its optimum mix of skills that match its skill requirements. As such, it is expected that even firms with outward labour mobility signal a healthy labour force.

H1 Firms' performance should be positively related to their in-degrees.
H2 Firms' performance should be positively related to their out-degrees.

The intensive inter- and intra industry mobility of workers inside labour clusters imply that clusters contain workers with superior knowledge and related skills that make them quite flexible from one firm to another. As such firms located inside LFN clusters can easily satisfy their demand for specific labour and, hence, benefit from improved performance.

H3 Firms inside clusters should perform better than those outside clusters.

Since MNEs provide exposure to unprecedented and rich knowledge that differs from the internal context (Ebersberger et al., 2011), firms that have access to such knowledge should benefit.

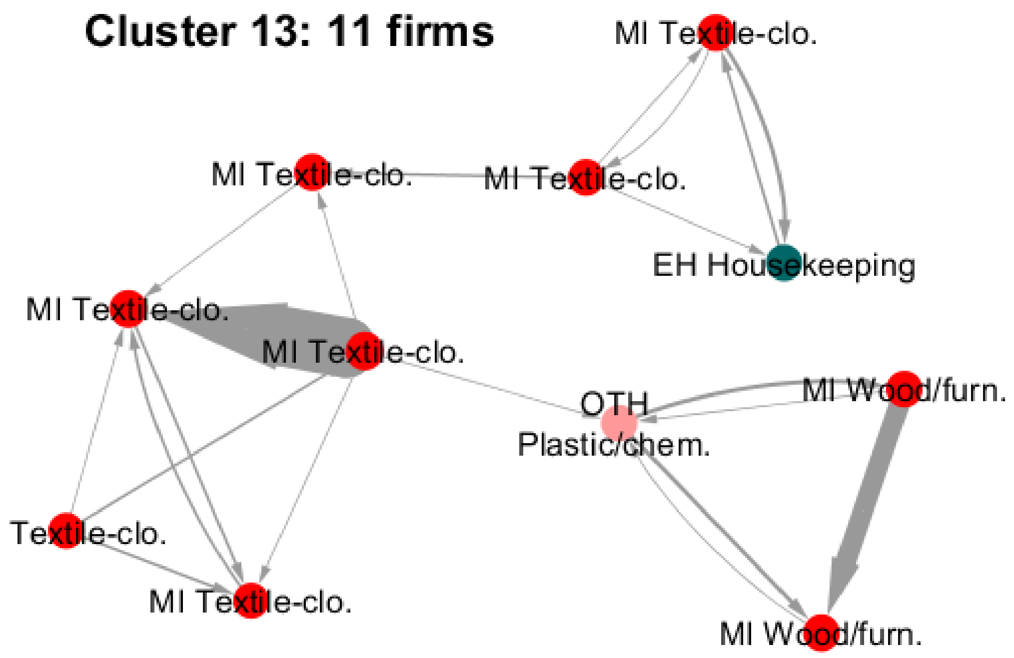


Figure 17. Cluster 13

H4 Firms in clusters that include MNEs should perform better than those in clusters without MNEs.

The use of network data in regression makes their estimations difficult due to the non-normal nature of the their distributions. Bootstrapped linear techniques that make no prior assumptions about the distribution is suitable for this purpose (Fox, 2015). Endogeneity is another issue that is taken care of by taking lagged dependent variables. Network data are often highly correlated; to take care of collinearity, in- and out-degrees are modelled separately. The following regression equation is estimated by bootstrapping over 1000 times:

$$\begin{aligned} Performance_i^t = \alpha_0 + \beta_1 Conn_i^{t-1} + \beta_\gamma Netstats_i \\ + \beta_2 DMNE_i^{t-1} + \beta_3 DClust_i^{t-1} + \beta_4 DClustMNE_i^{t-1} \\ + \beta_5 Size_i^{t-1} + \beta_6 LabourC_i^{t-1} + \beta_\theta \mathbf{Sectors}_i^{t-1} + \epsilon_i^t \end{aligned}$$

The models test whether the independent variables at time $t-1$ can predict $Performance$ of firm i at time t, i.e., 2014. The dependent variables are measured by revenue per worker ($rev\_$), added value per worker ($add\_$) and turnover per worker ($turn\_$) with the suffixes deg, in and out for the three different models with total degrees, in-degrees and out-degrees respectively. These firms performance data are retrieved from the AIDA database. The sample of firms in this empirical exercise includes both firms that experience and do not experience mobility. A brief description of the explanatory variables are outlined below:

(1) $Conn_i$ represents firms' connectivities: total degrees, Deg_i, indegrees, $InDeg_i$

and outdegrees, $OutDeg_i$ of firm i.

(2) $Netstats_i$ are a set of network statistics as follows: *ClustCo*, *AvShPath*, *NeighConn*, *BetwCent* refer to the clustering coefficient, average shortest path, neighbourhood connectivity and betweenness centrality for each firm i respectively.

(3) $DMNE_i$ is a dummy for whether firm i is a multinational.

(4) $DClust_i$ is a dummy for whether firm i is located inside a labour cluster as identified in section 4.4.

(5) $DClusMNE_i$ is a dummy for whether firm i is located in a labour cluster that also contains MNEs.

(6) $Size_i$ is firm size measured by average employment in the year 2012-2014. Employment is calculated by summing all individual employment contract for each firm.

(7) $LabourC_i$ is cost of labour as measured by staff costs per employee in 2013 retrieved from AIDA database.

(8) $\mathbf{Sectors}_i$ is a set of controls for the 12 different industries excluding the industry of interest, i.e, MI. They are Advanced tertiary services, Agriculture, Construction, Financial services, Leisure-Retail, Metalworks-Mechanical engineering, Mining-quarrying, Other industries, Other services, Housekeeping-education-health, Utilities and Wholesale-logistics in order of appearance in the table.

All the models perform well with reasonably good R^2 but the model with productivity as the dependent variable performs better. An increase in the number of total connections a firm has, has a positive effect on firms performance for all models. Separately, in-degrees and out-degrees, positively influence all performance measured. Thus, H1 is confirmed so that a greater variety in firms incoming links, in-degrees, is related to improved performance. H2 is aslo verified as the positive and significant coefficients on the variable out-degree confirm that out-mobility, exit of workers, is also an indicator of good firm performance.

There is weak evidence that an increase in a firm's intensity of relationship with other firms, clustering coefficient (*ClustCo*), is detrimental to its performance but the result is only significant for the model rev_out. Contrarily, there is strong evidence that an increase in average shortest path (*AvShPath*) is negatively related to firm performance; this implies that firms that are less reachable have decreasing productivity. However, this result only holds for models with out-degrees so that reachability becomes insignificant when the firm is recruiting. Similarly, the effect of the variable neighbourhood connectivity is different for models with in- and out-degrees. An increase in neighbourhood connectivity improves performance for the model with out-degree but it deters performance for the model with in-degrees. Betweenness centrality has a negative role on performance.

MNEs perform better than other firms as reported by the highly significant positive coefficient on the dummy $DMNE$. The claim that performance of firms that are inside labour clusters should be positive is not supported by the data as shown by the negative coefficient on the variable *DClust*; high labour mobility or flexible labour between highly-connected firms is detrimental to performance but it is not statistically significant[8]. H3 is rejected. This result suggests that recruiting from a set of "known" and "similar" firms does not add to firm productivity but rather keeps the firm locked-in.

However, there is consistent evidence across the models that firms in clusters that include MNEs perform better as reported by the positive and significant coefficient of the

[8]When the model is run with only mobile firms the result becomes statistically significant and the coefficient remains negative

Table 9. Impact of LFN structure and MNEs on firms' performance

	rev_deg	rev_in	rev_out	add_deg	add_in	add_out	turn_deg	turn_in	turn_out
Deg	0.246*			0.0760*			0.118*		
	(15.01)			(9.33)			(9.37)		
InDeg		0.274*			0.0755*			0.115*	
		(18.85)			(9.99)			(10.02)	
OutDeg			0.260*			0.102*			0.168*
			(12.18)			(9.83)			(9.90)
ClustCo	-0.213	-0.254	-0.429*	0.0597	0.0474	0.0608	-0.251	-0.268	-0.252
	(-1.14)	(-1.40)	(-2.63)	(0.69)	(0.55)	(0.70)	(-1.52)	(-1.60)	(-1.53)
AvShPath	-0.0940*	-0.0157	-0.102*	-0.0265*	-0.00287	-0.0535*	-0.0312*	0.00584	-0.0780*
	(-7.91)	(-1.47)	(-7.55)	(-4.14)	(-0.47)	(-6.62)	(-3.40)	(0.67)	(-6.68)
NeighConn	-0.000612	-0.00502	0.0302*	-0.00529	-0.00501	0.00827*	-0.0111*	-0.0104*	0.00996*
	(-0.10)	(-0.89)	(6.24)	(-1.59)	(-1.59)	(2.70)	(-2.21)	(-2.15)	(2.33)
BetwCent	-0.504^{+}	-0.431	-0.558^{+}	-0.424*	-0.396^{+}	-0.401*	-0.292	-0.251	-0.259
	(-1.70)	(-1.43)	(-1.78)	(-2.01)	(-1.84)	(-1.97)	(-0.93)	(-0.76)	(-0.81)
DMNE	0.667*	0.665*	0.701*	0.234*	0.234*	0.232*	0.448*	0.449*	0.443*
	(9.47)	(9.12)	(11.74)	(8.28)	(8.62)	(8.11)	(9.93)	(9.50)	(9.53)
DClust	-0.122	-0.179	-0.161	-0.0428	-0.0449	-0.0733	-0.0811	-0.0827	-0.142
	(-1.02)	(-1.46)	(-1.49)	(-0.85)	(-0.85)	(-1.52)	(-0.91)	(-0.95)	(-1.60)
DClusMNE	0.294*	0.303*	0.175	0.132*	0.135*	0.128*	0.186^{+}	0.190^{+}	0.182
	(2.13)	(2.07)	(1.26)	(2.28)	(2.26)	(2.25)	(1.69)	(1.71)	(1.64)
Size	-0.284*	-0.286*	-0.261*	-0.0452*	-0.0449*	-0.0436*	-0.145*	-0.144*	-0.143*
	(-47.94)	(-47.36)	(-47.39)	(-12.50)	(-12.39)	(-11.49)	(-28.55)	(-29.31)	(-28.16)
LabourC	0.517*	0.515*	0.521*	0.570*	0.570*	0.569*	0.514*	0.513*	0.513*
	(44.47)	(44.85)	(50.06)	(50.68)	(51.78)	(53.04)	(46.01)	(45.43)	(45.18)
Ad. tert	-0.0836	-0.0879	-0.0825	-0.0249	-0.0251	-0.0224	0.0594	0.0593	0.0628
	(-1.23)	(-1.25)	(-1.29)	(-0.61)	(-0.61)	(-0.52)	(0.99)	(1.01)	(1.11)
Agric.	-0.477*	-0.473*	-0.408*	-0.186*	-0.186*	-0.189*	-0.350*	-0.349*	-0.355*
	(-17.69)	(-17.61)	(-16.67)	(-12.94)	(-13.16)	(-13.09)	(-17.94)	(-18.68)	(-17.73)
Constru.	-0.327*	-0.325*	-0.253*	-0.178*	-0.171*	-0.163*	-0.175*	-0.162*	-0.157*
	(-10.79)	(-10.54)	(-9.07)	(-10.11)	(-10.94)	(-10.17)	(-7.29)	(-7.02)	(-7.07)
Fin. svs.	-0.133*	-0.131*	-0.154*	-0.0236^{+}	-0.0231^{+}	-0.0245^{+}	-0.166*	-0.165*	-0.167*
	(-5.37)	(-5.38)	(-6.41)	(-1.86)	(-1.83)	(-1.93)	(-9.42)	(-9.66)	(-9.45)
Lei.Ret.	-0.423*	-0.420*	-0.209*	0.0269	0.0274	0.0245	-0.123	-0.122	-0.127
	(-3.35)	(-3.33)	(-2.47)	(0.33)	(0.34)	(0.30)	(-1.48)	(-1.46)	(-1.42)
Metalwk.	0.220*	0.221*	0.221*	0.289*	0.289*	0.289*	0.231*	0.231*	0.230*
	(3.50)	(3.48)	(3.59)	(7.68)	(7.71)	(7.73)	(4.53)	(4.71)	(4.48)
Mining	-0.820*	-0.820*	-0.794*	-0.124*	-0.124*	-0.126*	-0.528*	-0.527*	-0.530*
	(-30.52)	(-30.78)	(-31.33)	(-8.37)	(-8.50)	(-8.72)	(-26.25)	(-26.09)	(-25.59)
Oth. ind.	-0.735*	-0.733*	-0.716*	-0.0191	-0.0187	-0.0211	-0.415*	-0.414*	-0.419*
	(-11.13)	(-10.98)	(-12.76)	(-0.54)	(-0.52)	(-0.58)	(-8.00)	(-8.20)	(-8.26)
Oth. svs.	-0.409*	-0.409*	-0.403*	-0.286*	-0.286*	-0.286*	-0.188*	-0.188*	-0.188*
	(-14.80)	(-15.44)	(-16.02)	(-18.75)	(-19.23)	(-19.09)	(-9.92)	(-9.70)	(-9.45)
Hth. edu.	0.282*	0.282*	0.297*	0.0124	0.0126	0.0119	0.404*	0.404*	0.403*
	(11.00)	(11.28)	(12.03)	(0.93)	(0.99)	(0.89)	(20.76)	(21.79)	(20.51)
Utilities	-0.717*	-0.720*	-0.704*	-0.0507*	-0.0509*	-0.0497*	-0.443*	-0.443*	-0.442*
	(-20.19)	(-20.55)	(-20.86)	(-2.18)	(-2.23)	(-2.06)	(-15.17)	(-15.24)	(-14.49)
Who. Log	-0.788*	-0.791*	-0.833*	-0.267*	-0.267*	-0.266*	-0.546*	-0.547*	-0.545*
	(-24.03)	(-25.37)	(-28.66)	(-15.17)	(-15.35)	(-15.07)	(-23.27)	(-23.83)	(-23.25)
Observations	41657	41657	44725	38898	38898	38898	40707	40707	40707
R^2	0.231	0.233	0.253	0.346	0.347	0.346	0.261	0.261	0.261

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$
predictors are at time t 2013-2014; dependent variables at $t + 1$
the sample includes firms with mobile and non-mobile workers

variable $DClusMNE$. H4 is confirmed. It can be argued that MNEs generate positive spillovers in clusters where they are present. Firm size is detrimental to performance as evidenced by the statistically significant and negative coefficient on the variable $Size$. Note that the average firm is of only 14 employees. As expected, an increase in expenditure on labour results in an increase in firm performance. The coefficients on the industry dummies reveal that only metalwork-mechanical and health-education-public administration sectors perform better than the made-in-Italy industry.

To conclude, labour mobility contributes positively to firm performance regardless of whether mobility is inward or outward. This result suggest that the firm is looking for its optimal mix of skills and mobility (in and out) is an adjustment mechanism through which this selection takes place. Despite the fact that workers may eventually leave, firms should, nevertheless, be encouraged to invest in these workers because of the positive spillovers they have on other firms and ultimately on the labour market. However, the results clearly indicates that mobility within a "standardised" setting, such as within a labour cluster, impoverishes the firm. Thus, "non-local" labour mobility together with variety in firms connections are important variables for performance. Moreover, MNEs tend to play a crucial role in raising the quality of labour clusters. This suggests that there are positive spillovers emanating from MNEs to local firms.

6. Conclusion

This research analyses only firm-to-firm labour mobility, that is, mobility of first-time workers, therefore, individuals that have never worked before, such as, school-leaving students are not observed. Within firm flows are excluded from this analysis as it would not add much to the research given that occupational data are not available. Thus, any interpretation of the results should take these issues into account. On the job made-in-Italy labour mobility in the Veneto region is 12 out of 100 workers (9 out of 100 for MNEs). The most mobile workers grouped by type of work-contracts are those on staff-lease contracts and those on other short-term contracts. The role played by job agencies in facilitating labour mobility is remarkable; however, the effectiveness of these agencies in matching workers and jobs is a topic that requires further research as such a high mobility may be due to dissatisfaction with the given matching.

Low-skilled workers change jobs more frequently than higher-skilled ones and workers with more than 3 years work-experience with an employer are immobile. The latter result is of concern as it signals some form of rigidity that could be the source of prolonged unemployment in times of crisis. Policies should aim at making experienced workers more flexible by regular training. In general, the MI sector shrunk (firing more than hiring), it lost workers to leisure services and retail sector, health, education, personal services and agriculture. This result is in line with current studies reporting the dismantling of manufacturing jobs into pre- and post-production jobs that are outsourced to manufacturing-related industries (IfM, 2016). Different types of work contracts imply different mobility rates where a stable contract is associated with high mobility inside MI rather than inter-sectoral mobility. Contracts of a temporary nature have the converse effect. However, different level of skills appear to be equally mobile pointing to the diversity in skills requirements of different firms.

Inferring from skill-relatedness, it is found that the made-in-Italy sector is highly-related to leisure-retail, logistics-wholesale and agriculture, a result that can orient policy-making decisions. In particular, such knowledge can facilitate and quicken intra-regional redeployment actions following crises. Ex ante, it can inform entrepreneurs as to potential diversification strategies. Finer disaggregation reveals that the intensity of labour flows is high to and from the made-in-Italy *textile*, *food* and *woodwork* industries.

This research outlines a few stylised facts about labour flow networks. In particular, the power-law nature of degree distributions is confirmed but it holds mainly for in-degree distributions so that there exists a few firms that hire proportionately more workers than the standard others. Network analysis reveals the hierarchical organisation of interfirm labour flows and the preference for workers to move from low-connected to high-connected firms and vice-versa, i.e. disssortativity. A non-spatial approach to identify clusters shows that labour flow clusters exhibit similar inter-sectoral characteristics except for a few, such as, flows within the *tanning* industry, where specific skills are still essential.

Empirical analysis reveal that the more connected a firm is with other firms the better is its performance and it does not matter whether the firm's connection is due to recruiting or firing. This paper claims that each firm is aiming at achieving an optimal mix of skills through the mechanism of labour reallocation so that the more mobility it generates the better chance it has to improve its performance. As such, at the firm and industrial level emphasis should be placed on investing in human capital regardless of contract duration and the possibility of workers leaving because mobility generates spillovers in the labour market and the firm will eventually benefit. However, this research points to the detrimental effect of getting locked into standardised or "local" connections. This result is important for micro-policies and firms should be encouraged to recruit workers "out-of-the-box" as variety in a firm's connections is beneficial.

The role of MNEs in host economies is still a highly debated subject today. This paper uncovers the positive influence of MNEs on the local labour market so that their presence generates collective increase in performance of the cluster. The reason behind this benefit is due to the newness and variety brought in by the foreign MNE. The exchange of labour with local firms leads to transfer of this external knowledge to the local firms. Policies should definitely aim at attracting MNEs as their presence in a labour cluster tends to improve the quality of the local labour market. Further research is needed to ascertain that these effects persist over time and across regions.

References

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

Barabási, A.-L. and others (2009). Scale-free networks: a decade and beyond. *science*, 325(5939):412.

Borgatti, S. P., Mehra, A., Brass, D. J., and Labianca, G. (2009). Network analysis in the social sciences. *Science*, 323(5916):892–895.

Boschma, R. (2005). Proximity and Innovation: A Critical Assessment. *Regional Studies*, 39(1):61–74.

Clauset, A., Shalizi, C. R., and Newman, M. E. J. (2009). Power-law distributions in empirical data. *SIAM Review*, 51(4):661. 02049.

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, 35(1):128–152.

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

Dahl, M. (2002). Embedded knowledge flows through labor mobility in regional clusters in Denmark. In *DRIUD Summer Conference on "Industrial Dynamics of the New and Old*

Economy–who is embracing whom. Citeseer.
Davis, S. J. and Haltiwanger, J. (2014). Labor market fluidity and economic performance. Technical report, National Bureau of Economic Research.
Diodato, D. and Weterings, A. B. R. (2015). The resilience of regional labour markets to economic shocks: Exploring the role of interactions among firms and workers. *Journal of Economic Geography*, 15(4):723–742.
Ebersberger, B., Lehtoranta, O., and Herstad, S. (2011). Bridging the global and the local? Multinational enterprises, labor market mobility and localized learning. In *56th Annual ICSB World Conference, Stockholm, June*, pages 15–18.
Eriksson, R. and Lindgren, U. (2009). Localized mobility clusters: impacts of labour market externalities on firm performance. *Journal of Economic Geography*, 9(1):33–53.
Fornahl, D., Zellner, C., and Audretsch, D. B. (2004). *The role of labour mobility and informal networks for knowledge transfer*. Springer Science & Business Media. Google-Books-ID: TeQAccTtB9YC.
Fox, J. (2015). *Applied regression analysis and generalized linear models*. Sage Publications.
Fujita, S. (2015). Declining labor turnover and turbulence. *Federal Reserve Bank of Philadelphia Working Paper Series No.15-29*.
Gabe, T. M. and Abel, J. R. (2012). Specialized knowledge and the geographic concentration of occupations. *Journal of Economic Geography*, 12(2):435–453.
Gianelle, C. (2014). Discovering the regional small world of labour mobility. evidence from linked employer–employee data. *Regional Studies*, 48(7):1263–1278.
Guerrero, O. A. and Axtell, R. L. (2013). Employment growth through labor flow networks. *PLoS ONE*, 8(5):e60808.
Hyatt, H. R. and Spletzer, J. R. (2013). The recent decline in employment dynamics. *IZA Journal of Labor Economics*, 2(1):1–21.
IfM (2016). Manufacturing metrics review report. Manufacturing Metrics Expert Group, Institute for Manufacturing.
Keilbach, M. C. (2012). *Spatial knowledge spillovers and the dynamics of agglomeration and regional growth*. Springer Science & Business Media.
Lissoni, F. (2001). Knowledge codification and the geography of innovation: the case of Brescia mechanical cluster. *Research Policy*, 30(9):1479–1500.
Maliranta, M., Mohnen, P., and Rouvinen, P. (2009). Is inter-firm labor mobility a channel of knowledge spillovers? Evidence from a linked employer–employee panel. *Industrial and Corporate Change*, 18(6):1161–1191.
Malmberg, A. and Power, D. (2005). (How) do (firms in) clusters create knowledge? *Industry and Innovation*, 12(4):409–431.
Maslov, S. and Sneppen, K. (2002). Specificity and Stability in Topology of Protein Networks. *Science*, 296(5569):910–913.
Masys, A. J. (2016). Disrupting terrorist and criminal networks: Crime script analysis through dodaf applications. In Masys, A. J., editor, *Exploring the Security Landscape: Non-Traditional Security Challenges*, Advanced Sciences and Technologies for Security Applications, pages 231–247. Springer International Publishing. DOI: 10.1007/978-3-319-27914-5_11.
Melo, P. C. and Graham, D. J. (2014). Testing for labour pooling as a source of agglomeration economies: Evidence for labour markets in England and Wales. *Papers in Regional Science*, 93(1):31–52.
Neffke, F. and Henning, M. (2012). Skill relatedness and firm diversification. *Strategic Management Journal*, 34(3):297–316.
OECD (2009). How do industry, firm and worker characteristics shape job and worker flows? In *OECD Employment Outlook 2009*, pages 117–163. OECD Publishing.
Poole, J. P. (2013). Knowledge transfers from multinational to domestic firms: Evidence from worker mobility. *Review of Economics and Statistics*, 95(2):393–406.
Power, D. and Lundmark, M. (2004). Working through knowledge pools: labour market dynamics, the transference of knowledge and ideas, and industrial clusters. *Urban studies*,

41(5-6):1025–1044.
Ravasz, E. (2003). Hierarchical organization in complex networks. *Physical Review E*, 67(2).
Serafinelli, M. (2015). 'Good' firms, worker flows and local productivity. Working Paper Series 15-29, The Rimini Centre for Economic Analysis.
Tsai, W. (2001). Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. *Academy of management journal*, 44(5):996–1004.
Watts, D. J. and Strogatz, S. H. (1998). Small world. *Nature*, 393:440–442.
Zimmermann, K. F. (2005). European labour mobility: Challenges and potentials. *De Economist*, 153(4):425–450.

Appendix A. Tables of statistics

Table A1. Total and change in employment for all firms including firms without mobility in 2012 and 2013

Sectors	2012	2013	Change	Average	Rank
Advanced tertiary	88,517	86,894	-2%	87,706	7
Agriculture	23,648	23,780	1%	23,714	11
Construction	99,895	93,935	-6%	96,915	6
Financial ser.	50,527	50,216	-1%	50,372	10
Leisure/retail	248,814	240,101	-4%	244,458	2
Made-in-Italy	187,538	181,791	-3%	184,665	4
Metalworks	202,935	200,953	-1%	201,944	3
Mining/quarrying	1,696	1,551	-9%	1,624	13
Other industries	68,108	66,560	-2%	67,334	9
Other services	74,437	74,733	0%	74,585	8
Services to the person	325,870	331,195	2%	328,533	1
Utilities	16,614	16,640	0%	16,627	12
Wholesale/logistics	173,851	170,670	-2%	172,261	5
Total	1,562,450	1,539,019	-1%	1,550,735	
Number of Firms	297,151	297,526	0%		
Total number of unique firms over the period 2012-2013				**330409**	

Table A2. Matrix of skills and contract type (in percentage) for all employed workers in 47706 firms

	High	Medium	Low	Non	Total
Permanent	0.24	0.30	0.31	0.14	**619,761**
Apprentice	0.17	0.48	0.31	0.04	**28,534**
Fixed-term	0.27	0.32	0.22	0.19	**78,336**
Staff-lease	0.12	0.29	0.42	0.17	**12,207**
On-call	0.13	0.64	0.09	0.14	**26,219**
Domestic	0.01	0.22	0.01	0.75	**2,006**
Project-based	0.64	0.26	0.03	0.07	**22,202**
Internships	0.25	0.39	0.11	0.26	**9,083**
Total	**198,412**	**254,821**	**228,190**	**116,925**	**798,348**

Table A3. Relatedness of MI to other sub-sectors: average, in and out

Sectors	**rank**	**rank_in**	**rank_out**
AS Culture/publish.	28	26	29
AS IT services	22	19	24
AS Professional ser.	10	9	16
AS R&D	34	32	34
AS Telecommu.	33	33	32
Agriculture	4	4	4
Construction	6	5	11
EH Diverse ser.	9	10	12
EH Education	16	23	9
EH Health/social	14	20	10
EH Housekeeping	3	2	5
EH Public admin.	17	21	13
EH Repairs/rentals	21	14	21
FN Credit	31	30	31
FN Finance/ins.	27	28	28
LR Retail	2	3	2
LR Tourism	1	1	1
MET Electric. mach.	18	18	18
MET Mechanical eq.	15	13	17
MET Metalworks	7	7	6
MET Transport veh.	23	22	22
Mining-quarry.	32	31	33
OS Cleaning	11	16	8
OS Real estate	20	15	20
OS Rental ser.	30	29	30
OS Surveillance ser.	12	11	14
OTH Building mat.	25	27	25
OTH Other ind.	26	24	26
OTH Paper-printing	19	17	19
OTH Pharmaceut.	29	34	27
OTH Plastic/chem.	13	12	15
Utilities	24	25	23
WL Transport/log.	8	8	7
WL Wholesale	5	6	3

Table A4. Number of firms, flows and MNEs in clusters together with skills, contracts and education statistics of firms in these clusters

					Skills				**Contracts**				**Education**			
Cluster	Firms	Flows	MNEs	Main sectors	High skill	Med skill	Low skill	No skill	Permanent	Internship	Fixed-term	Staff-lease	No edu	Compulsory edu	Diploma	Degree
1	68	267	1	Food, Textile, Metalwork	11%	21%	50%	18%	15%	2%	43%	36%	1%	33%	54%	12%
2	46	218	4	Wood, Food, Footwear	25%	2%	57%	16%	11%	1%	17%	71%	1%	43%	50%	5%
3	39	243	0	Tanning	4%	2%	84%	9%	4%	1%	5%	86%	4%	84%	10%	1%
4	35	355	0	Tanning	1%	2%	90%	7%	3%	1%	5%	91%	10%	72%	14%	1%
5	33	99	0	Food, Footwear	2%	5%	61%	32%	27%	2%	39%	27%	10%	45%	35%	5%
6	32	73	3	Footwear	8%	7%	75%	10%	44%	3%	23%	26%	15%	49%	32%	4%
7	32	99	4	Food, Footwear, Textile	22%	15%	49%	13%	18%	0%	13%	65%	2%	38%	28%	30%
8	23	105	0	Textile, Transport	1%	11%	66%	21%	16%	0%	50%	27%	23%	34%	30%	6%
9	19	107	0	Tanning, Food	11%	12%	50%	26%	7%	0%	23%	57%	10%	30%	49%	6%
10	16	93	0	Tanning	1%	2%	87%	9%	11%	0%	2%	87%	3%	70%	14%	0%
11	14	60	0	Food, Cleaning svs	15%	5%	55%	25%	3%	0%	43%	52%	0%	67%	23%	10%
12	14	33	2	Eyewear	18%	3%	39%	39%	0%	0%	3%	97%	3%	24%	61%	12%
13	11	90	0	Textile	0%	1%	99%	0%	90%	0%	9%	0%	53%	47%	0%	0%