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Relatedness, industrial branching and technological cohesion in U.S. metropolitan areas

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RELATEDNESS, INDUSTRIAL BRANCHING AND TECHNOLOGICAL COHESION IN U.S. METROPOLITAN AREAS

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ABSTRACT: This paper builds on and complements work by evolutionary economic geographers on the role of industry relatedness for regional economic development and extends this work into a number of methodological and empirical directions. First, while recent work defines relatedness through co-occurrence, this paper measures relatedness as intensity of input-output links between industry pairs. Second, this measure is employed to examine industry evolution in 360 U.S. metropolitan areas over the period 1977-1997. The paper confirms the findings of existing work: Industries are more likely to be members of and enter and less likely to exit a metropolitan industry portfolio if they are technologically related to those industries. Third, based on average industry relatedness in a metropolitan area, an employment weighted measure of metropolitan technological cohesion is developed. Changes in technological cohesion can then be decomposed into selection, entry and exit effects revealing that the change in technological cohesion is not only due to the entry and exit of related industries but employment growth in strongly related incumbent industries.

Keywords: Evolutionary economic geography; industry relatedness; industrial branching; technological cohesion; selection; entry; exit;

INTRODUCTION

Regions evolve through a process of creative destruction of technological and industrial variety (Schumpeter 1939; Storper and Walker 1989; Essletzbichler and Rigby 2005; Rigby and Essletzbicher 2006; Neffke et al. 2011b) mirroring rapid churning at the plant level (Davis et al. 1996; Baldwin 1998, Foster et al. 1998). Creative destruction reflects an imperfect trial and error process where firms enter markets with the hope to sell products at a profit. Evidence for the U.S. manufacturing sector indicates that between 1963 and 1982, 39.8 percent of manufacturing firms registered in a particular census year were not yet active five years earlier. Those high entry rates where matched by slightly lower exit rates varying between 30.8 and 39.0 percent (Dunne et al. 1988). Underpinning long-term structural change, the high rates of churning at the national level are also observed at the state and metropolitan area levels (Rigby and Essletzbichler 2000; Essletzbichler and Rigby 2002). While some regions are able to harness the process to rejuvenate their industrial base others fail to diversify and become locked into a process of industrial decline (Grabher 1993; Hassink and Shin 2005; Martin 2010).

Martin and Sunley (2006) discuss a number of ways for regions to create new paths of development, including processes of recombinant innovation (Frenken et al. 2012) based on existing industrial or technological diversity, investment and technology transfer from outside the region (Bathelt et al. 2004) and technological change and endogenous transformation of firms in the region (Tödtling and Trippl 2004). How regions grow and decline is also a key research question in new geographical economics. Debates in economics have centered on the relative importance of urbanization and localization economies to generate regional and urban economic growth. The importance of urban diversity to generate novel ideas and knowledge through spillovers among different rather than similar industries leading to urban economic growth was famously advocated by Jane Jacobs (1969) but has since been examined empirically by economists (Glaeser et al. 1992; Henderson et al. 1995; Duranton and Puga 2001; Rosenthal and Strange 2004) complementing their work on the impact of localization economies and urban size. Numerous empirical studies on the importance of diversity versus specialization as drivers of regional and urban economic growth produced inconclusive evidence at best (Beaudry and Schiffauerova 2009; De Groot et al. 2009). Perhaps one reason for this inconclusive evidence is the treatment of industries as quantitatively distinct but qualitatively similar. Localization economies enter empirical models as absolute or relative concentration of employment in any industry ignoring the (dis)similarity of those industries. Similarly, urbanization economies are approximated through urban size, population density or the number of plants with little regard for the relationship among sectors making up those regions.

One of the recent contributions of the work by evolutionary economic geographers is the importance attributed to the concept of relatedness between industries highlighting the need to consider not only the number and employment shares of regional industries but also the similarity among them to understand regional economic evolution. While sectoral diversity may increase the potential for radical innovations because of the exchange of different ideas, too much dissimilarity between sectors may impede knowledge exchange because some overlap in knowledge bases and competences is required to communicate effectively. Noteboom (2000) thus postulates a trade-off between diversity and similarity: too much similarity may result in cognitive lock-in while too little similarity may impede knowledge exchange altogether. The notion of cognitive distance points towards the idea of relatedness between sectors and forces researchers to capture the technological similarity between sectors empirically rather than simply tallying the number of sectors or employment shares in sectors.

Industries are related through different channels of information and knowledge exchange: labor flows, supplier-customer relationships and knowledge "spillovers" (Marshall 1890; Potter and Watts 2012). Geographic proximity is assumed to facilitate this exchange. Cities with local pools of skilled labor are more likely to boost firm performance (Boschma et al. 2009) and regional economic growth. As firms are more likely to diversify into industries requiring similar skill sets to take full advantage of their workforce (Neffke and Henning 2013) and workers are more likely to exchange information if they possess related skills, cities are likely to add industries employing workers with related skill sets. The second channel of knowledge exchange is through supplier-customer linkages as the presence of competent suppliers increases the productivity of their customers, while the presence of competent customers push up competition and innovation among suppliers. Thus regions are likely to branch into related industries as those industries can take advantage of the local supplier and customer base (Frenken and Boschma 2007). And finally, technology spillovers may be more likely to occur between technologically related industries, rather than within a single industry or between technologically unrelated industries (Boschma and Frenken 2011).

In order to examine the impact of the relatedness on regional performance, Frenken et al. (2007) distinguished between "related" and "unrelated" variety and linked it to regional employment, output and productivity growth. Employing an entropy measure of industry concentration, "related variety" refers to the concentration of employment in SIC[1]-5-digit sectors within SIC-2-digit sectors and "unrelated variety" referred to the concentration of employment in SIC-2-digit sectors. Their findings indicate that for Dutch regions "related variety" is positively related to employment growth, while "unrelated variety" is negatively related to unemployment growth suggesting the operation of a portfolio effect. Boschma and Iammarino (2009) found similar results for Italian regions. Building on entropy based measures of variety, Boschma et al. (2009) show the importance of related skill portfolios of a plant's workforce for its productivity growth in Sweden, Quatraro (2010) demonstrated that related but not unrelated variety exerted a positive impact of TFP growth in Italian regions and Boschma et al. (2012) find positive effects on value added and employment growth in Spanish regions. Hartog et al. (2012) find that the positive effect of related variety on employment growth in Finnish regions is restricted to high technology sectors only.

Subsequent work developed relatedness measures based on co-occurrences of country exports (Hidalgo et al. 2007), co-production of products in plants (Neffke and Svensson Henning 2008), and co-citation of patents in patent applications (Rigby 2013). Hausmann and Klinger (2007) and Hidalgo et al. (2007) establish a link between a country's export portfolio and its subsequent potential for economic development as countries expand their export portfolio into industries related to their

[1] SIC: Standard Industry Classification

existing export mix. Countries of the Global North occupying densely connected parts of the product/industry space have thus better opportunities to diversify into new industries than countries of the Global South. The lack of opportunities to diversify into a large number of sectors then impedes rapid growth and catch up processes. The impact of complementary knowledge flows through labor mobility has been examined by Boschma et al. (2009) who demonstrated that firm productivity increases only if workers with complementary rather than different or identical skills are hired. They show that hiring workers with identical skills actually decreases firm productivity suggesting that only the import of related knowledge results in competitive advantages.

Because complementary knowledge flows bridge existing, but different knowledge and technology fields, Frenken and Boschma (2007) and Boschma and Frenken (2011) suggested that regions diversify into industries related to the existing portfolio of industries. New, but related forms of knowledge and organizational routines can be generated through spin-off dynamics (Klepper 2007; Boschma and Wenting 2007), new firm entry in related industries, inflow of labor with complementary skills or the co-location of suppliers and/or customers to take advantage from learning by doing, learning by using and learning by interacting (von Hippel 1995). Regional branching into related industries suggests a gradual build up of technological and industrial variety not dissimilar to Darwin's notion of speciation and evolution driven primarily by gradual change[2]. The branching of regions into related manufacturing industries has been studied systematically for 170 Swedish regions (Neffke et al. 2011a). Using a measure of relatedness based on co-occurrence of different products in firms, Neffke et al. (2011a) highlight substantial change in regional industrial structure over a 30 year period driven by entry of industries related to existing industries in the region and exit of less related industries from the region.

This paper builds on and complements this work as follows. First, the paper attempts to corroborate empirically the findings of Neffke et. al (2011a) in a different geographic context and with a different measure of relatedness. The different mechanisms of knowledge exchange identified above require different measures of relatedness that will in turn capture one particular channel linking sectors. Although the impact of different measures of relatedness on the process of regional branching may differ in magnitude, by sector and metropolitan areas, theory suggests that the general result of regional evolution as industrial branching into related industries should hold independently of the channel of knowledge transfer and relatedness measure studied. It is important to notice that the focus on a single measure of relatedness impedes a proper evaluation of the sources of differences in results, whether differences are due to different empirical implementation of relatedness or different economic-geographic contexts. The measure of technological relatedness employed in this paper is developed from input-output flows between 362 US manufacturing industries. This measure is applied to examine the impact of technological relatedness on the entry and exit of new industries in 360 U.S. metropolitan areas over the period 1977-1997. The second contribution of the paper is an analysis of the main components of change in metropolitan technological cohesion. Change in technological cohesion is shown to be the result of changes in

[2] Exploring the existence of critical threshold effects to generate rapid regional transformations would be an interesting study of research and could point towards regional evolution as punctuated equilibria rather than gradual change.

technological relatedness among incumbent industries, selection or differential growth of incumbent industries, and the entry and exit of industries. While Neffke et al. (2011a) focus on the entry and exit of industries as drivers of structural change in regions resulting in relatively stable patterns of regional technological cohesion over time, the reallocation of employment towards better connected incumbent industries may also contribute to the evolution of technological cohesion that may result in negative technological lock-in if not counterbalanced by industry entry.

The paper is structured as follows: Section 2 briefly outlines different approaches to measuring relatedness and explains how relatedness is measured in the context of this paper. Section 3 discusses the empirical findings linking relatedness to structural change and technological cohesion in 360 metropolitan areas. Section 4 discusses an employment share weighted measure of metropolitan technological cohesion and decomposes change in technological cohesion into selection, entry and exit effects. Section 5 concludes the paper.

MEASURING INTER-INDUSTRY RELATEDNESS

Three broad approaches to measure relatedness are distinguished in the literature (Neffke and Henning 2013): The first one relies on the hierarchy of industry classifications and defines industries that fall into the same broad industry classes as related. For instance, SIC-4-digit industries belonging to the same SIC-2-digit industry are considered as related. This is the approach chosen by Frenken et al. (2007), Boschma and Iammarino (2009), Boschma et al. (2009), Quatraro (2010), Boschma et al. (2012) and Hartog et al. (2012). This method is relatively easy to implement and available for a large number of secondary data for different countries and regions. However, the method is criticized on theoretical grounds, as classification of industries into broader industry groups does not necessarily mean that the industries are related technologically or knowledge is exchanged more easily between those sectors.

The second strategy that gained popularity in the recent literature defines relatedness primarily through co-occurrence measuring relatedness between two industries by examining whether they are often found together in the same economic entity. This work includes the co-occurrence of industries in a country's or region's export portfolio (Hidalgo et al. 2007; Boschma et al. 2013), the likelihood of co-production of different products in the same plant said to reveal economies of scope through technological spillovers (Neffke and Svensson Henning 2008; Neffke et al. 2011a) or the co-occurrence of patent citations (Jaffe 1986; Rigby 2013). However, co-occurrence assumes technological or cognitive proximity leading to co-production or diversification into related products/sectors and obscures the sources of economies of scope that may emerge from co-occurrence. As a result it is difficult to determine the type of relatedeness that has been measured (Neffke and Henning 2013).

The third approach defines relatedness through similarity in resource use or flow of resources between firms and/or sectors focusing on the role of human capital and the similarity in occupation profiles (Farjoun 1994; Dumais et al. 1998), technological resources using patent analysis (Jaffe et al. 1986; Breschi et al. 2003), and material resources using commodity flows measured through input-output linkages (Fan and

Lang 2000; Feser 2003). Resource based similarity measures suffer from bias because of the strategic relevance given to some resources. Patent based indicators shed light on relatedness among patent-intensive industries, while input-output analysis may be more useful for an investigation of manufacturing rather than service industries. Each of the approaches has advantages and disadvantages and the utility of them in various historical, geographical and sectoral contexts needs to be explored further through systematic accumulation of empirical material.

In order to examine whether resource based measures result in similar conclusions on the link between relatedness and regional industrial branching, this paper follows the literature on input-output relations and adopts a measure of relatedness based on the relative strengths of value flows between pairs of industries[3]. The inter-industry relatedness measure is derived from the 'Make Table' and 'Use Table' of the detailed 1987 benchmark input-output tables supplied by the Bureau of Economic Analysis (BEA) that include input-output flows between 563 industries. The 'Make Table' includes the value of commodities c, produced by Industry i. The 'Use Table' contains the value of commodities c consumed by Industry i. In order to obtain value flows between industries (rather than commodities that are produced by several industries) the following transformation was carried out. First, the 'Make Table' was used to find out how much of a commodity c was produced by various industries i. More specifically, s_{ic}, refers to the share of one unit of commodity c produced by industry i. Second, the 'Use Table' was required to reveal the value, F_{cj}, of commodity c consumed by industry j. In order to obtain the value flows between industries i and j, F_{cj} was multiplied by the industry-commodity shares s_{ic}. Third, summing the resulting values over industries i and j then yields an estimate of Input-output flows, F_{ij} between industries i and j in US$. Following Fan and Lang (2000), the input-output relatedness between industries i and j, IOR_{ij}, is measured as:

$$IOR_{ij} = \frac{1}{2}\left(\frac{F_{ij}}{\sum_{j=1}^{n} F_{ij}} + \frac{F_{ji}}{\sum_{i=1}^{m} F_{ji}} \right) \quad (1)$$

One of the drawbacks of Input-output tables is the lack of detailed industry classifications for non-manufacturing industries. Hence, the analysis was restricted to the 362 manufacturing sectors (IO Industry numbers 130100 - 641200) included in the BEA input-output tables. Unfortunately those 362 IO industry numbers are only a subset of the 453 SIC codes used in census statistics. Because some IO numbers correspond to various SIC codes (eg. 141900 (Sugar) corresponds to SIC codes 2061, 2062 and 2063), the SIC sectors were aggregated to the IO industries resulting in a 362x362 industry matrix[4].

[3] As one of the reviewers pointed out, this paper contributes a novel empirical analysis to the existing set of studies on industrial branching but is unable to offer a clear conclusion on the origin of diverging results from other studies as not only the measure of relatedness but also the geographic and temporal contexts vary.
[4] In this analysis industry relatedness is held constant over the whole period to facilitate the component of change analysis. Treating relatedness as a dynamic concept is left for future investigation.

This measure of IO-industry relatedness can now be used to examine the role of industry relatedness on structural change in the US space economy. As it is generally assumed that metropolitan areas most closely mirror functional economic spatial entities, the empirical analysis uses 360 US metropolitan statistical areas[5]. In order to examine structural change in those metropolitan areas and the components of change of regional technological cohesion, it was necessary to identify the presence or absence of industries in a metropolitan area. County business patterns provide this information. For each year, they include information on employment, number of plants and annual payroll for SIC-4-digit sectors per county. For confidentiality reasons, employment figures for small industries in small counties are often omitted and replaced with employment size bands. However, using the information on the number of plants in different plant size categories (which is not suppressed), Isserman and Westervelt (2006) suggested a data-imputation method that reduces substantially the uncertainty in county-industry employment numbers. Following Isserman and Westervelt (2006), data imputation has been carried out for all years of the analysis to reduce the uncertainty in county-industry-employment figures. The second potential data problem arises from a change in industry classification system between 1987 and 1988. In order to analyze structural change, consistent industry classifications are required. A consistent set of industries between 1977 and 1997 was obtained by converting 1972 SICs into 1987 SICs using the Bartelsman-Becker-Gray conversion tables[6]. Unfortunately a more severe reclassification took place in 1997. Despite existing conversion tables, the new NAICS industry classification system is entirely different from the old SIC system such that consistency over time is compromised and the analysis presented in this paper is restricted to the 20 year period from 1977-1997. For this period, a consistent set of 362 manufacturing industries for 360 metropolitan areas has been constructed.

Combining the data on IO-relatedness from the BEA input-output tables and industry employment data from the County Business Patterns allows for analysis of the impact of industry relatedness on structural change in metropolitan areas.

STRUCTURAL CHANGE AND TECHNOLOGICAL COHESION IN US METROPOLITAN AREAS

Before examining structural change in metropolitan areas, Figure 1 reveals the IO relatedness between 362 manufacturing sectors in 1987. In order to facilitate readability, the relatedness measure IOR_{ij} has been reduced to three categories using the values for the 90^{th} (0.237) and 75^{th} (0.024) percentile as cut-off criteria. The white cells are those with an IOR_{ij} measure of less than 0.024, the light blue values represent those industry pairs with IOR_{ij} values between 0.024 and less than 0.237, while the dark blue represent those industry pairs with values of >=0.237. There are a number of clusters along the main diagonal (food, textile/apparel) and some industries which are tied to most other industries (such as metallurgy and machine tools, petroleum refining, industrial inorganic and organic chemicals). Interestingly electronics is related primarily to other electronic and electrical products but is not as strongly linked throughout the product space as expected.

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[5] For a complete list and definition of metropolitan areas see http://www.census.gov/population/metro/data/metrodef.html

[6] http://www.nber.org/nberces/

FIGURE 1 ABOUT HERE

As the main objective of the paper is to uncover the extent of structural change at the metropolitan level, Figure 2 depicts the change in metropolitan industry composition between 1975 and 1997. The solid line represents the share of industries in metropolitan areas that were present in those areas in 1975. The original set of industry-regions in 1975 constitutes 77.2% of metropolitan industries in 1997. Or put another way, a quarter of industries that were present in 1975, disappeared from metropolitan industry portfolios by 1997. The dashed line represents the share of industries in metropolitan areas that were present in 1997 and reveals that only 61.0% of industry-regions present in 1997 existed in 1975. These values are similar to those observed for the Swedish case reported by Neffke et al. (2011a).

FIGURE 2 ABOUT HERE

The IOR measure reports the relatedness between industry-pairs. As metropolitan areas host more than one industry, it is necessary to examine how strongly a single industry in a metropolitan area is related to all other industries that make up a regional portfolio. A regional portfolio of region *r*, RPF_r, in any given year is defined as the set of industries with non-zero employment in the region. In order to count links to closely related industries only, the number of links to industries with IOR values above a certain threshold are counted. The closeness of a particular industry *i* to all other industries *j* comprising a regional portfolio *r* is then defined as

$$closeness_{ir} = \sum\nolimits_{j \in RPF_r} I(IOR_{ij} > 0.237) \quad (2),$$

where I(.) is an indicator function that takes the value 1 if the argument is true and 0 if the argument is wrong. Any threshold value could be used to obtain the closeness index. 0.237 is somewhat arbitrary but has been chosen because it constitutes the 90% percentile, i.e. ten percent of industry-pairs have IORij values >0.237[7].

For each region, technological cohesion is then defined as average closeness value of industries present in a regional portfolio:

$$Technological\ cohesion_{\mathrm{r}} = \frac{1}{N_r} \sum\nolimits_{i \in RPF_r} closeness_{ir} \quad (3),$$

where N_r is the number of industries belonging to regional portfolio RPF_r. Figure 3 depicts the technological cohesion of regional portfolios for the years 1977, 1982, 1988 and 1992 (solid line)[8]. In addition, the dotted line depicts the average closeness of industries belonging to a regional portfolio to all industries that are not part of the regional portfolio.

FIGURE 3 ABOUT HERE

[7] Notice that substituting these relatedness values with the original IORij values or a threshold value of 0.024, the 75th percentile, does not produce qualitatively different results from those presented here. The logistic regression results are presented in Table A.1 in Appendix.

[8] 1988 rather than 1987 was chosen as starting year of the third period in order to eliminate a potential impact of the industry reclassification on entry and exit rates.

According to Neffke et al. (2011a) a regional portfolio is considered to be cohesive if the average closeness of industries to the RPF industries is higher than to industries that are not part of the RPF (regions are considered cohesive if the solid line is above the dotted line). According to Figure 3, regional portfolios are, on average, cohesive and stable over time. This stability seems somewhat at odds with the turnover of industries depicted in Figure 2. It is thus useful to examine how the entry and exit of industries influences the technological cohesion of a regional portfolio. Entrants are defined as industries that entered over a five-year period while exits are defined as industries that exited over a five year period[9]. The average closeness of entrants to the portfolio of industries in regions they enter is represented by upward facing triangles while the average closeness of exits is represented by diamonds. Entrants tend to be closer to the regional portfolio of industries than industries that remain outside the region suggesting that regions diversify into industries that are related to the existing industrial base. But entrants are less related to the regional portfolio members than the incumbent portfolio members suggesting that entrants are complementing rather than simply reproducing the existing industry structure. Entry weakens the technological cohesion of regional portfolios and may be important for regions to avoid negative lock-in (see also Table 4 below). Exits tend to be more closely related to the regional portfolio than industries that are not part of the regional portfolio suggesting that they are not entirely unrelated to the regional portfolio they have been part off. But exits are less close to the regional portfolio of industries than the industries remaining in the portfolio which suggests that industries that are less close to their regional portfolio are less likely to benefit from knowledge spillovers and hence, more likely to exit a region. Because the technological cohesion of exits is lower than the technological cohesion of the remaining regional portfolio industries, exit improves the overall cohesion of a region (see also Table 4 below). Notice that there is little difference in the technological cohesion of entrants and exits. While entrants are closer to the regional portfolio in 1977, exits are closer to the regional portfolio in 1992. The differences between the closeness values of entrants and exits are not statistically significant in 1982 and 1988 (see Figure 3). This is different from the Swedish case, where the technological cohesion of entrants is considerably higher than the technological cohesion of exits and much closer to the technological cohesion of regional portfolio members. But overall, the results are similar despite the fact that relatedness is measured differently and the economic-geographic context differs for the two cases. More specifically, the three main sets of findings identified by Neffke et al. (2011a) are broadly substantiated: First, regional portfolios are technologically cohesive and remain so over time. Second, industries are more likely to enter a region if they are technologically related to the existing regional portfolio of industries. Third, industries that are less closely tied to the regional portfolio than other portfolio members, are more likely to exit the industry. These three findings are examined in further detail next.

We can formally define membership, entry and exit as

$$member_{ir}^{t} = I(i \in RPF(r,t)) \quad (4)$$

[9] Experiments with one-year periods did not alter the conclusions of the results.

$$entry_{ir}^{t+5} = I(i \notin RPF(r,t) \wedge i \in RPF(r,t+5)) \qquad (5)$$

$$exit_{ir}^{t} = I(i \in RPF(r,t) \wedge i \notin RPF(r,t+5)) \qquad (6)$$

The member variable takes on a value of 1 if industry *i* was part of regional portfolio RPF_r at time *t* and 0 if it was not part of RPF_r. The entry variable takes on a value of 1 if industry *i* was not part of regional portfolio RPF_r in year *t* and was part of RPF_r in year *t+5*. The exit variable takes on a value of 1 if industry *i* was part of regional portfolio RPF_r in year *t* and was no longer part of RPF_r in year *t+5*. Table 1 presents descriptive information of the dummy variables and the size of regions and industries. All tables are based on industry-metropolitan area observations pooled across four 5-year periods resulting in 521,280 (352 SIC x 360 metropolitan areas x 4 periods) observations for calculations involving the membership dummies. Because entry can only occur if industries were not present in a region in year *t*, the number of observations involving the entry dummy is reduced to a subsample of 356,454 industry-regions. These are the potential entry opportunities for industries. Because exit can only occur if industries were present in year *t*, the subsample for potential exit opportunities of 164,826 industry-regions was used for the calculation of descriptive statistics involving the exit dummy. Adding both subsamples results in the complete sample again.

Table 2 reveals the correlation coefficients between values for closeness and member, entry and exit dummies. While the relationship between closeness values and membership and entry dummies is positive, the correlation coefficient for exit is negative. Industries are more likely to be members of a regional portfolio and enter a metropolitan area if they are closely related to the existing portfolio while they are more likely to exit if they are less closely related to the portfolio. All correlation coefficients are statistically significant below the 0.0001 level.

In order to determine the economic importance of closeness, it is useful to examine how closeness affects the probabilities of membership, entry and exit. The probability of membership is 31.6 percent (total number of industry-regions that exist in year t (164,826) divided by the total number of potential industry-regions (521,280)), the probability of entry is 8.6 percent (the number industry-region entrants (38,690) divided by the total number of potential entry opportunities (356,454)) and the probability of exit is 14.5 percent (the number of actual exits (31,407) divided by the number of potential exits (164,826)). These probabilities can be calculated separately for different closeness values. Because of the large number of values that the closeness variable could assume, closeness values have been grouped into closeness classes with an interval width of 5 (eg. 0-4; 5-9, etc.) Figures 4a-c depict the probabilities of regional portfolio membership, entry and exit with increasing closeness values.

FIGURE 4 ABOUT HERE

Figures 4a and 4b reveal that the probabilities of membership and entry are well below average membership and entry probabilities for low closeness values and end up far above them for high closeness values. The probability of regional portfolio membership is more than five times as high for closeness values of 30 or more compared to membership probability for closeness values of 0-4. The relative frequency of entry is close to five times higher for closeness values of 30 or higher than the relative frequency for closeness values of 0-4. Figure 4c depicts the probabilities of exit and demonstrates that exit probabilities decrease from 22.7 percent for closeness values of 0-4 to 7.7 percent for closeness values of 30 or higher.

In order to control for potential confounding variables, Table 3 presents the results of logistic regression analysis with membership (models 1a-c), entry (models 2a-c) and exit (models 3a-c) dummies as dependent variables. Logistic regression rather than OLS is used because the dependent variables are binary variables (yes=1; no=0). Robust standard errors are reported in parentheses and odds-ratios are reported in brackets. Models 1a, 2a, 3a regress the closeness values of individual industries to the regional portfolio of industries on membership, entry and exit. Confirming the patterns from figures 4a-c, closeness is positively related to membership and entry, but negatively related to exit. The odds-ratios give an indication of how the odds of membership/entry/exit change after a unit change in the dependent variable (i.e. one additional link). An odds-ratio greater than one indicates an increase in the odds that the outcome is obtained while an odds-ratio of less than 1 indicates a decrease in the odds that an outcome is obtained when increasing the independent variable by one unit. Table 3 reveals that the odds of membership increase by 6.9 percent, the odds of entry by 3.7 percent and the odds of exit decrease by 3.1 percent if an industry's closeness to the regional portfolio increases by one additional link.

The membership, entry and exit dummies are likely to be influenced by the size of industries and regions. Large industries are more likely to be part of a regional portfolio and they are more likely to enter a region and less likely to exit a region. Larger metropolitan areas are able to sustain more industries and are more likely to attract new and retain existing industries. In order to control for size effects, the logarithm of total metropolitan employment and the logarithm (both with base 10) of total national industry employment has been included in models 1b, 2b, and 3b. Both variables have the expected signs in all models, but the parameter estimates for closeness declined. The size of industries and metropolitan areas will positively influence membership and entry independent of the relatedness of specific industries to the regional portfolio of industries. Ceteris paribus, they will also influence exit probabilities negatively. In order to get an indication of the size of the effects, it is useful to look at the odds-ratios again. The odds-ratios for industry and metropolitan size are similar. Keeping the effects of other independent variables constant, a one-unit increase in the size of a metropolitan area (equalling a ten-fold employment increase), will increase the odds of membership by 5.9, the odds of entry by 2.5 and decrease the odds of exit by 61.4%. Similarly, a one unit increase in the size of industry will increase the odds of membership by 5.1, the odds of entry by 2.9 and decrease the odds of exit by 60.5%. On the other hand, a unit change in the closeness variable would result in an increase in the odds of membership by 1.6 percent and the odds of entry by 1.4 percent, while it would decrease the odds of exit by 0.8 percent.

The probabilities of membership, entry and exit of an industry may also be influenced by its closeness to industry portfolios absent from the region as relatededness to industries in other regions may increase the probability of industries to exit from the regional portfolio and relocate to those regions. Models 1c, 2c and 3c thus add an industry's closeness to the portfolio of industries absent from the region to the model.

This variable is negatively related to member and entry probabilities and positively related to exit probabilities. Under ceteris paribus conditions, if a large number of related industries is absent from a region than membership and entry probabilities are lower and the probability of exit increases. Or in other words, other regions that host related industries are more likely to host, attract and retain those industries. The signs of the parameter estimates for closeness (RPF), metropolitan and industry size do not change with the inclusion of this variable although the odds ratios for closeness (RPF) and industry size increase somewhat and the odds ratios for the size of metropolitan areas decreases. The odds ratio for the closeness to industries absent from a region are relatively small, lowering the odds of membership and entry by 1.1 and 1.0 percent and increasing the odds of exit by 0.4 percent with an additional link to industries absent from the region.

The analysis shows the membership, entry and exit probabilities of individual industries to regional portfolios but do not explain the contribution of industry entry and exit to changes in regional technological cohesion overall. While Neffke et al. (2011a) conceptualize regional evolution as creative destruction through entry and exit of related industries, they do not consider selection effects. Entry and exit are probably the driving forces of change in the long-run, but the differential growth of industries will contribute to changes in regional technological cohesion in the short and medium run. The next section thus offers a decomposition of aggregate changes in metropolitan technological cohesion into selection, entry and exit effects.

COMPONENTS OF CHANGE IN TECHNOLOGICAL COHESION OF METROPOLITAN AREAS

In order to account for selection in addition to entry and exit effects on changes in technological cohesion, an employment weighted measure of technological cohesion is required. Rather than treating each industry equal as assumed in the previous analysis, the contribution of an industry to the technological cohesion of a metropolitan area not only depends on its closeness to the regional portfolio but also its metropolitan employment share. Furthermore, the closeness measure (see (2)) is in part influenced by the size of a metropolitan area and is expected to be higher in large metropolitan areas than in small metropolitan areas, as larger areas tend to sustain a larger number of industries and hence, the expected number of links of any single industry is higher in large metropolitan areas with a large number of industries to link to[10]. Because we want to have a look at the relative effects of entry, exit and incumbents on technological cohesion it is therefore useful to standardize the closeness of industry i to regional portfolio r by the number of industries in a region, N_r to obtain the standardized closeness measure, SC_{ir} where

$$SC_{ir} = \frac{closeness_{ir}}{N_r} \qquad (7)$$

The value of this measure can be interpreted as average link that an industry i has to all other regional portfolio members. Figure 5, depicts the average of SC_{ir} for

[10] Notice, that this was addressed through the inclusion of metropolitan size as independent variable in the regression analysis presented in Table 3.

industries belonging to a regional portfolio (solid line), industries absent from the regional portfolio (dashed line), entering (upward facing triangles) and exiting (diamonds) industries. While the result appears similar to the average closeness values depicted in Figure 3, entrants exhibit considerably higher standardized closeness values than exits (the differences between entry and exit are statistically significant at the 0.01 level for the periods 1977 and 1992, and at the 0.05 level for the periods 1982 and 1988).

FIGURE 5 ABOUT HERE

An employment weighted measure of metropolitan technological cohesion of metropolitan area *r* and at time t, WTC_r^t, is then defined as

$$WTC_r^t = \sum_i s_{ir}^t SC_{ir}^t \qquad (8)$$

where $s_{ir}^t = \frac{emp_{ir}^t}{\sum_i emp_{ir}^t}$ is the employment share of industry *i* in metropolitan area *r* at time *t*, divided by total manufacturing employment in the metropolitan area. Following the literature on productivity decomposition (Foster et al. 1998), the change in technological cohesion in metropolitan area *r* and between times *t* and *t+1* is then:

$$\begin{aligned} WTC_r^{t+1} - WTC_r^t = & \sum_{i \in INC} (SC_{ir}^{t+1} - SC_{ir}^t) s_{ir}^t + \sum_{i \in INC} (s_{ir}^{t+1} - s_{ir}^t)(SC_{ir}^t - WTC_r^t) + \\ & \sum_{i \in INC} (SC_{ir}^{t+1} - SC_{ir}^t)(s_{ir}^{t+1} - s_{ir}^t) + \sum_{i \in N} (SC_{ir}^{t+1} - WTC_r^t) s_{ir}^{t+1} - \sum_{i \in X} (SC_{ir}^t - WTC_{ir}^t) s_{ir}^t \end{aligned} \qquad (9)$$

The subscript *INC* denotes incumbent industries, industries that exist in *t* and *t+1*, *N* represents entering industries that exist in *t+1* but were not in operation in year *t*, and *X* denotes exiting industries, industries that were part of the regional portfolio in year *t* but were no longer present in the region in year *t+1*.

Aggregate change in technological cohesion of a metropolitan area can then be understood as the sum of five components. The first three components in (9) represent changes relating to incumbent industries, while the fourth component represents changes attributed to entrants and the fifth component represents changes attributed to exits. The first incumbent term measures the change in the standardized closeness values of incumbent industries assuming that employment shares of those industries remain constant. This term is usually interpreted as innovation effect in productivity studies, but here refers to the adaptation of the regional portfolio to the existing sets of industries. Because the relatedness between sectors, IOR_{ij} (see (1)) was kept constant over time, SC_{ir} can only change if the composition of the regional portfolio changes. Thus a positive “portfolio effect” means that the regional industry portfolio has become more closely related to its incumbent industries, i.e. the net effect of entry and exit results into a more coherent portfolio (assuming that the relative weight of incumbent industries is kept constant). The second term represents a selection effect. This term is positive if industries with standardized relatedness values higher than the value for the regional average (weighted technological cohesion) expand their employment shares relative to those that are less related to the regional portfolio than the average. The term is negative if less related industries expand market shares or if more related industries shrink. If industries do indeed benefit from their relatedness with other sectors in the metropolitan area, then we would expect selection to be positive. The third term is a covariance term which is positive if industries for which the regional portfolio of industries has become more closely related also expand their market shares. From an evolutionary point of view, the selection effect is the most interesting and meaningful of the three incumbent effects and as Table 4 illustrates it is also the most important of the three incumbent effects to explain aggregate change in technological cohesion. The entry term is positive if entering industries are more closely related to the regional portfolio than average. The exit term is negative if industries more closely related to the regional portfolio than average exit the metropolitan area and positive if less closely related industries exit the industry (the exit of less related industries increases metropolitan technological cohesion).

Table 4 depicts the average contributions of each component to average change in metropolitan technological cohesion for each of the four periods. The percentages (in parentheses) are based on the share of each component on the sum of the absolute values of the five components.

TABLE 4 ABOUT HERE

The employment weighted technological cohesion measure increased during all periods and growth was most pronounced in the periods 1977-1982 (2.87 percent) and 1992-1997 (2.78 percent).Although entry and exit contribute significantly to aggregate changes in technological cohesion in all periods (in particular up to the mid-1980s), selection effects are not negligible and selection was the most important effect from 1988 onwards. It is also noticeable that entry reduces technological cohesion, although the net effect of entry and exit results in an increase in cohesion save for the period 1992-1997. While industry entry and exit are important for shaping the metropolitan technological cohesion, the decomposition analysis also demonstrates that selection operating on incumbent industries constitutes an important evolutionary force, at least in the short and medium run. The analysis also demonstrates that high contributions of selection and exit results in increasing employment concentrations in related industries.

CONCLUSION

The paper contributes to the conceptual and empirical development in evolutionary economic geography focusing on the emergence and path dependent trajectory of technological and industrial variety (Boschma and Frenken 2006; Boschma and Martin 2010; Essletzbichler and Rigby 2010; Essletzbichler 2012). More specifically the paper complements and augments the literature on relatedness and the conceptualization of regional evolution as industrial branching process (Frenken and Boschma 2007; Neffke et al. 2012a). Rather than measuring relatedness through co-occurrence or exploiting information embedded in industry hierarchies, this paper attempted to corroborate the general findings of this literature with a relatedness measure based on the relative strength of input-output relations (Fan and Lang 2000).

One of the shortcomings of using a different relatedness measure is the inability to identify the sources of similarities and differences in results as they could arise from the properties of the respective relatedness measures or from differences in economic-geographic context (eg. differences in subsidies to keep unproductive industries alive, R&D programs to actively search for and attract new industries to a region, etc.).

Despite the differences in measurement and context, the paper confirms broadly the results of Neffke et al.'s (2011a) analysis of the Swedish manufacturing sector. First, the probabilities of metropolitan industry portfolio membership and entry to the portfolio are positively related to the closeness of those industries to their respective metropolitan industry portfolios, while exit probabilities increase with declining closeness to the metropolitan portfolio. Second, the average number of links of entrants and exits is smaller than the average number of links among metropolitan portfolio members. Thus, while entrants add technological variety and decrease technological cohesion, exits reduce technological variety and increase technological cohesion in a metropolitan area. Third, as a result of the combined entry and exit effects and despite considerable industry turnover, metropolitan technological cohesion remains relatively stable over time. While those results are broadly confirmed, the relative impact of relatedness on the probabilities of membership, entry and exit differs between the Swedish and U.S. case. More systematic comparative research is necessary to examine the origin of those differences.

In a second step, the paper then examined the impact of different forces behind changes in technological cohesion including selection, entry and exit. For this purpose, an employment weighted measure of technological cohesion was developed where not only relatedness but also the relative size of sectors was taken into consideration. Changes in employment weighted cohesion could then be decomposed into selection, entry and exit effects. While the entry/exit dynamic explains in part the evolution of metropolitan technological cohesion, selection effects are equally important in the U.S. case. Cities become more cohesive because the positive effect of exit on technological cohesion is larger than the negative effect of entry and because those industries that are more closely related to the metropolitan industry portfolio expand their employment shares relative to those that are not. Because of the variety reducing effects of selection and exit, entry is essential to inject novelty in metropolitan areas. The decomposition analysis demonstrates the importance of employment reallocation to related incumbent industries and the importance of entry to lower technological cohesion but does not answer the question whether technological cohesion, changes in cohesion or the contribution of individual components result in faster economic transformation or metropolitan growth.

The results point to a number of future research questions with important policy implications. First, while it is interesting to uncover the roots of path-dependent evolution in metropolitan areas, it is important to examine how the technological cohesion of metropolitan areas is linked to their performance including changes in employment and unemployment rates, productivity and output growth or the pace of technological change. Are regions that are more/less technologically cohesive expanding their market shares relative to those that are not? Second, detailed historical industry case studies could help examining the trajectories of individual metropolitan areas over time as performance is likely linked to particular metropolitan industry specializations (see also Hidalgo et al. 2007; Potter and Watts 2012). Are areas with industries occupying central locations in product space more likely to diversify into new industries and hence, rejuvenate their economies? Are those areas with industries occupying peripheral parts of the product space more likely to become locked into a declining regional trajectory and/or have less potential to create new evolutionary pathways? Third, a more careful analysis of the components of change for individual metropolitan areas may help identify the main bottlenecks for future economic development. If incumbent industries dominate a metropolitan area, selection pressures may result in negative lock in, while too much entry may result in technological incoherence and lack of knowledge spillovers between individual sectors. Fourth, the focus on branching into related industries paints a picture of gradual metropolitan evolution. However, cities often go through phases of rapid transformation and surges of economic growth that is difficult to reconcile with this image of gradual change. Hence, the identification of threshold effects or minimum levels of relatedness could prove important for regional path creation and needs to be investigated in future papers on regional evolution. Future work also requires an explicit analysis of the time frame over which we measure change as radical technological breakthrough will occur necessarily in one place or another over longer time frames. It certainly will require new methodological work as existing industry, product or skill classifications will be unable to shed light on radically new industries, products or skills not yet defined as such. Work also needs to take into consideration the fact that relatedness measures are based on actually observed and already made links but that they do exclude industry complementarities that are not yet exploited and hence detectable with those measures[11].

In this sense, the analysis presented in this paper complements and adds to the rapidly growing theoretical and empirical literature in evolutionary economic geography on the role of relatedness for the creative destruction of regional and metropolitan economies and points towards the need for theoretical refinement and systematic comparative empirical work to understand the influence of different relatedness measures, time frames and geographic context on the empirical findings.

[11] I would to thank one of the reviewers to point this out as this is an important methodological question that will need addressing especially when examining change over long time frames.

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TABLES AND FIGURES:

Table 1: Descriptive statistics

Variable	Number of observations	Mean	SD	Minimum	Maximum
Member	521,280	0.32	0.46	0.00	1.00
Entry	356,454	0.09	0.28	0.00	1.00
Exit	164,826	0.14	0.35	0.00	1.00
Closeness (PF_r)	521,280	13.83	15.96	0.00	273.00
Closeness (non-PF_r)	521,280	22.28	26.31	0.00	280.00
Log10(emp_r)	521,280	4.21	0.56	2.31	6.10
Log10(emp_i)	521,280	4.43	0.48	2.98	6.04

Notes: Observations refer to industry-region combinations. Variables: Member: membership dummy variable; Entry: entry dummy variable; Exit: exit dummy variable; Closeness (PF_r): the number of closely related industries present in a metropolitan area; Closeness (non-PF_r): the number of closely related industries that are absent from the metropolitan area; Log10(emp_r): The logarithm (base 10) of total employment in metropolitan area r; Log10(emp_i): The logarithm (base 10) of total employment in industry i; The values for the entry and exit dummies are based on restricted samples.

Table 2: Correlation between the values for closeness and the membership, entry and exit dummy variables

	Correlation	p-value	N
Member	0.3411	<0.0001	521,280
Entry	0.1498	<0.0001	356,454
Exit	-0.1271	<0.0001	164,826

Note: The correlation coefficients for entry and exit are based on restricted samples.

Table 3: Logistic regression analysis of the probabilities of membership, entry and exit

Dependent variables →	Membership			Entry			Exit		
Model	1a	1b	1c	2a	2b	2c	3a	3b	3c
Closeness (PF)	0.067*	0.016*	0.030*	0.037*	0.014*	0.025*	-0.031*	-0.008*	-0.012*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[1.069]	[1.016]	[1.031]	[1.037]	[1.014]	[1.026]	[0.969]	[0.992]	[0.988]
Log10[emp(r)]		1.777*	1.462*		0.903*	0.658*		-0.952*	-0.861*
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
		[5.911]	[4.315]		[2.468]	[1.931]		[0.386]	[0.423]
Log10[emp(i)]		1.62*	1.740*		1.058*	1.164*		-0.928*	-0.976*
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
		[5.079]	[5.697]		[2.879]	[3.204]		[0.395]	[0.377]
Closeness (non-PF)			-0.006*			-0.010*			0.004*
			(0.000)			(0.000)			(0.000)
			[0.989]			[0.990]			[1.004]
Constant	-1.700*	-15.914*	-15.024*	-2.786*	-10.940*	-10.696*	-1.219*	6.937*	6.643*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log-likelihood	-290054.9	-252124.2	-250133.1	-101949.9	-98174.1	-97761.4	-66163.7.5	-63545.9	-63485.2
Number of observations	521,280	521,280	521,280	356,454	356,454	356,454	164,826	164,826	164,826

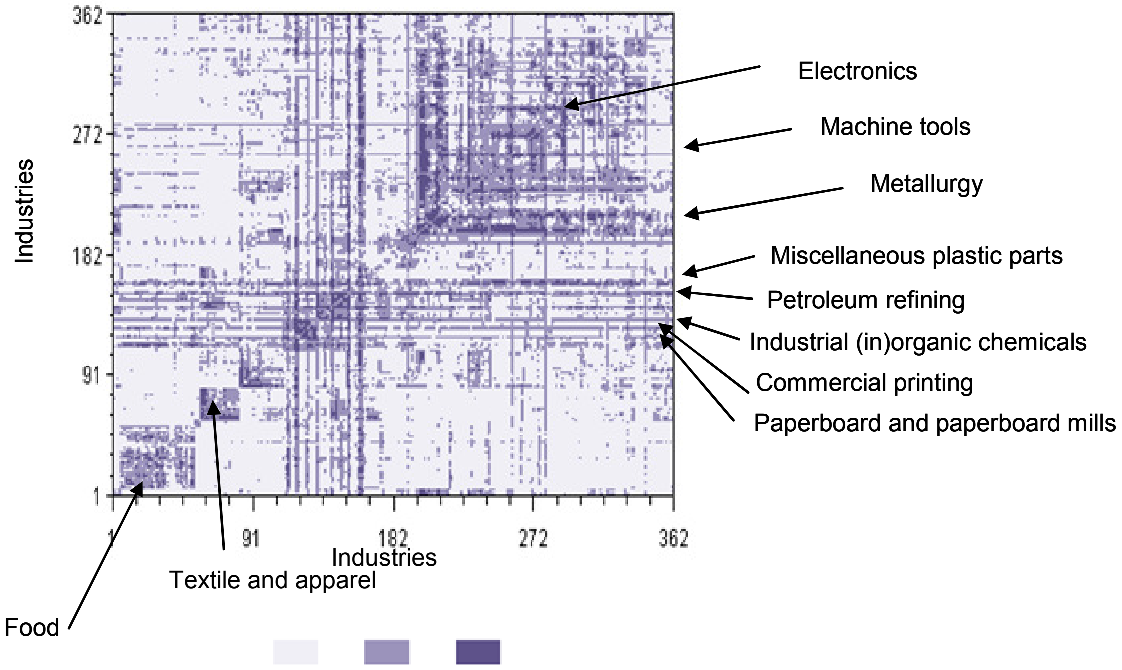
Notes: Robust errors are shown in parentheses. Odd-ratios are shown in brackets. Independent variables: Closeness (PF): The number of closely related industries in the region; Log10[emp(r)]: The logarithm (base 10) of total manufacturing employment in a metropolitan area; Log10[emp(i)]: The logarithm (base 10) of total US employment in the industry; Closeness (non-PF): The number of closely related industries absent from regions. Dependent variables: Membership = 1 if an industry is found in the regional portfolio in year t. Entry=1 if an industry is found in the regional portfolio in year t+5 but not year t. Exit=1 if an industry is found in the regional portfolio in year t, but not in year t+5. t=1977, 1982, 1988, 1992. 1988 has been chosen as starting year for period 3 in order to avoid any remaining inconsistencies from changes in industry classifications between 1987 and 1988. However, using 1987 instead of 1988 did not alter the conclusions of the results.

Table 4: The components of change in employment weighted metropolitan technological cohesion, 1977-1997

Period		Change in Metropolitan Technological Cohesion	"Portfolio"	Selection	Covariance	Entry	Exit
1977-1982	Δ	0.00525	0.00112	0.00256	0.00044	-0.00171	-0.00284
	%	(2.87)	(12.90)	(29.58)	(5.06)	(-19.73)	(-32.73)
1982-1987	Δ	0.00145	-0.00074	0.00165	0.00006	-0.00155	-0.00202
	%	(0.77)	(-12.23)	(27.49)	(1.05)	(-25.69)	(-33.54)
1988-1992	Δ	0.00325	-0.00119	0.00399	-0.00013	-0.00124	-0.00182
	%	(1.69)	(-14.20)	(47.63)	(-1.60)	(-14.80)	(-21.77)
1992-1997	Δ	0.00543	0.00112	0.00501	-0.00030	-0.00302	-0.00262
	%	(2.78)	(9.31)	(41.52)	(-2.47)	(-25.01)	(-21.69)

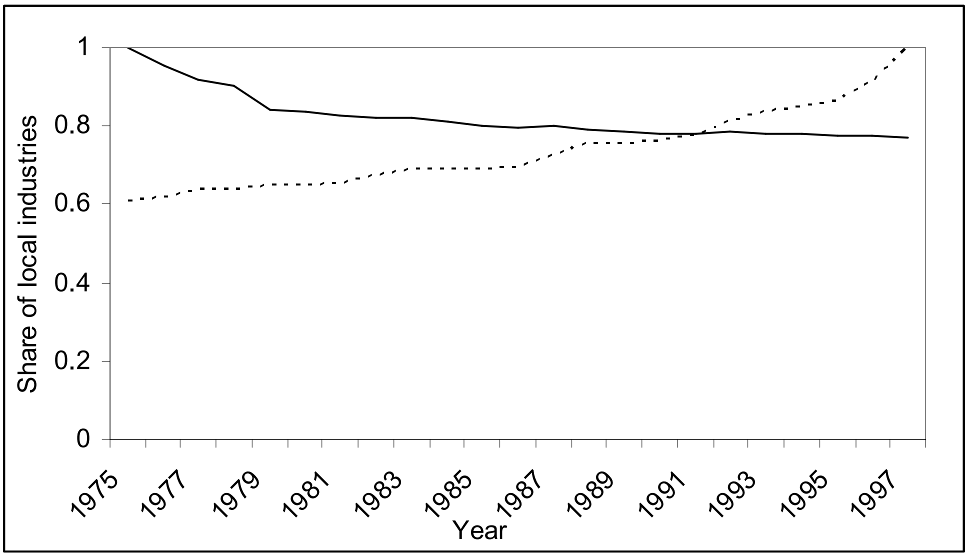
Note: The percentages for aggregate change represent rates of change for each period. The percentages for the individual components refer to the share of each component on the sum of the absolute values of each component.

Figure 1: Relatedness matrix based on 1987 input-output table



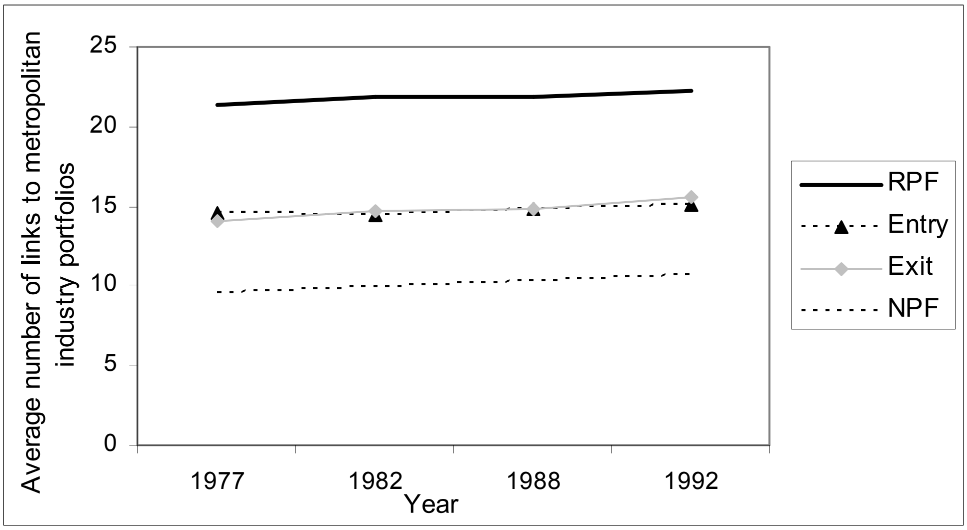
Notes: IOR: 90 percentile = 0.237; 75th percentile = 0.024;
Dark purple: IOR values >=0.237; medium dark purple: 0.0237<=
IOR values < 0.24; light purple: IOR values <0.024.

Figure 2: Structural change in U.S. metropolitan areas, 1975-1997



Notes: The solid line represents the shares of industries present in a metropolitan area in 1975. The dashed line represents the shares of industries present in a metropolitan area in 1997.

Figure 3: The evolution of metropolitan technological cohesion



Notes: The vertical axis depicts the average number of related industries (IOR>0.237) (see (3)) averaged over all metropolitan areas. The solid line depicts the values for regional portfolio members; The dashed line depicts the closeness of absent industries to the regional portfolio members; The line with the upward facing triangles depicts the closeness of entrants and the line with diamonds depict the closeness of exits to the regional portfolio. Notice that values for entry are significantly higher than the values for exit in 1977 and significantly lower than exit in 1992. The differences in 1982 and 1988 are not statistically significant.

Figure 4: Probabilities of membership, entry and exit

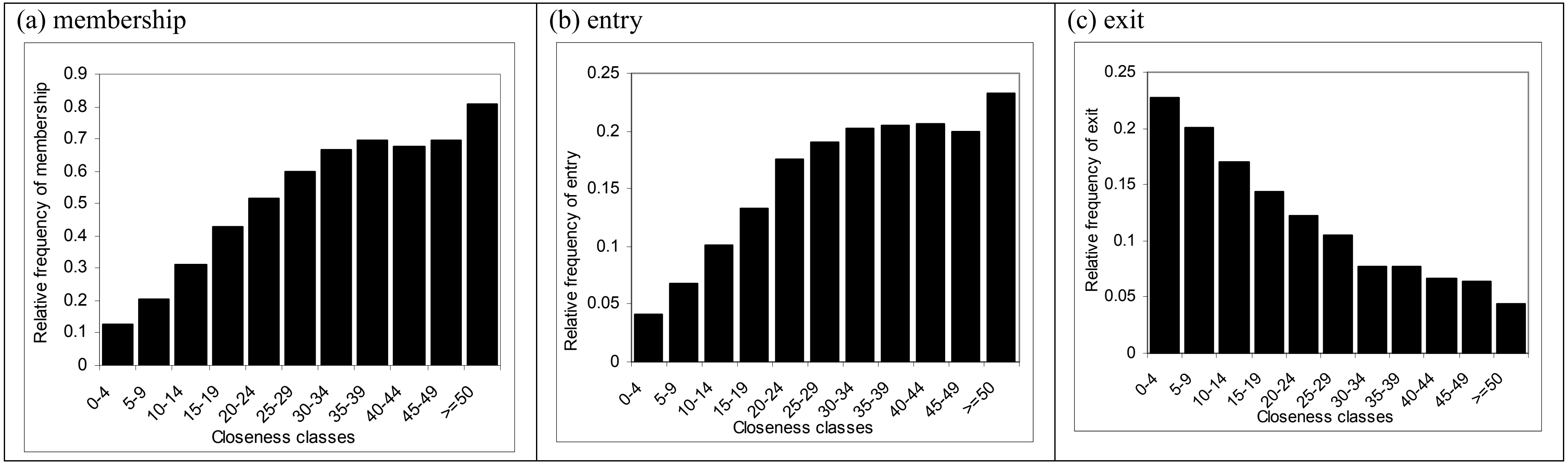
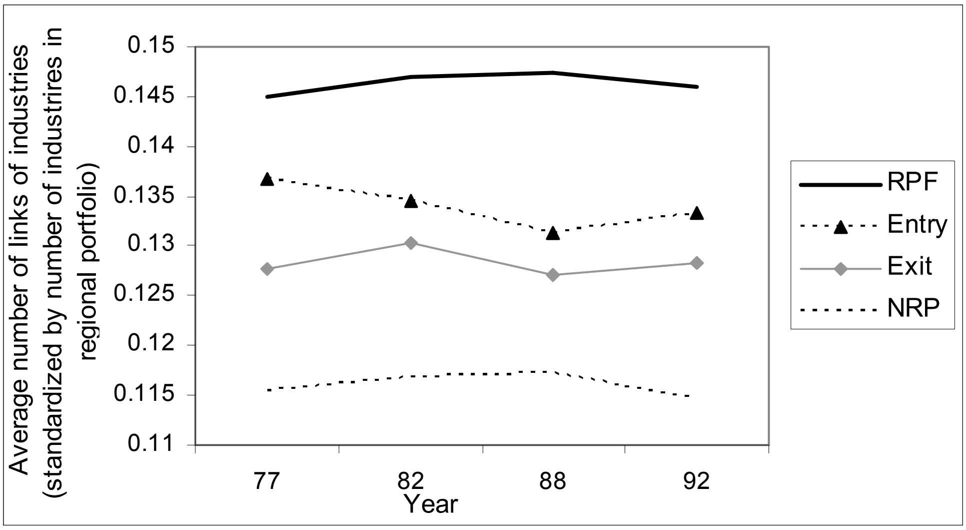


Figure 5: The evolution of standardized metropolitan technological cohesion



Notes: The vertical axis depicts the average number of links of an industry to regional portfolio members standardized by the number of industries in a regional portfolio (see (7)) and averaged over all metropolitan areas. The solid line depicts the values for regional portfolio members; The dashed line depicts the closeness of absent industries to the regional portfolio members; The line with the upward facing triangles depicts the closeness of entrants and the line with diamonds depict the closeness of exits to the regional portfolio. Notice all values are statistically significantly different from each other at the 0.01 level with the exception of entry and exit in 1982 and 1988 where the difference is only significant at the 0.05 level.

Table A.1: Logistic regression analysis of the probabilities of membership, entry and exit

Dependent variables →	Membership			Entry			Exit		
Model	1a	1b	1c	2a	2b	2c	3a	3b	3c
Closeness (PF)	0.036*	0.011*	0.019*	0.022*	0.011*	0.017*	-0.017*	-0.005*	-0.008*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[1.037]	[1.011]	[1.019]	[1.023]	[1.011]	[1.017]	[0.983]	[0.995]	[0.992]
Log10[emp(r)]		1.610*	1.133*		0.737*	0.416*		-0.880*	-0.697*
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
		[5.002]	[3.105]		[2.089]	[1.516]		[0.415]	[0.498]
Log10[emp(i)]		1.563*	1.758*		0.992*	1.132*		-0.904*	-1.005*
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
		[4.772]	[5.801]		[2.697]	[3.102]		[0.404]	[0.366]
Closeness (non-PF)			-0.007*			-0.005*			0.003*
			(0.000)			(0.000)			(0.000)
			[0.993]			[0.995]			[1.003]
Constant	-2.024*	-15.086*	-13.746*	-3.006*	-10.124*	-9.261*	-1.013*	6.496*	6.084*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log-likelihood	-278651.23	-251027.0	-248271.8	-100541.6	-97774.6	-97345.9	-65482.8	-63500.6	-63362.3
Number of observations	521,280	521,280	521,280	356,454	356,454	356,454	164,826	164,826	164,826

Notes: Robust errors are shown in parentheses. Odd-ratios are shown in brackets. Independent variables: Closeness (PF): The number of closely related industries in the region; Log10[emp(r)]: The logarithm (base 10) of total manufacturing employment in a metropolitan area; Log10[emp(i)]: The logarithm (base 10) of total US employment in the industry; Closeness (non-PF): The number of closely related industries absent from regions. Dependent variables: Membership = 1 if an industry is found in the regional portfolio in year t. Entry=1 if an industry is found in the regional portfolio in year t+5 but not year t. Exit=1 if an industry is found in the regional portfolio in year t, but not in year t+5. t=1977, 1982, 1988, 1992. 1988 has been chosen as starting year for period 3 in order to avoid any remaining inconsistencies from changes in industry classifications between 1987 and 1988. However, using 1987 instead of 1988 did not alter the conclusions of the results. Industries are considered related if IOR_{ij}>=0.024, such that the top 25 percent of industry pairs are considered related.