

A Unidirectional Measure of Industry Relatedness and its Application to Acquisitions Framework. (September 2018)

Author Details: ⁽¹⁾Elena Cefis, PhD-Full Professor-Dep. of Management, Economics and Quantitative Methods University of Bergamo, Italy ⁽²⁾Damiana Rigamonti, Department of Economics and Business Economics, Aarhus BSS, Aarhus University

Abstract-*This paper proposes an index to measure the industry relatedness between an origin firm and a target firm. It is an operational instrument able to determine the direction of flows in relationships among an origin firm and a target firm belonging to industrial sectors or macro-sectors (regardless of their definition), where the directionality of these flows matters, such as acquisitions, collaborations, alliances. It can be used in empirical analyses at the firm level in order to capture industry relatedness as an independent variable or as a weight factor. The index is based on the observed co-occurrences and accounts of the direction of the dyad origin-target in the relationship of interest. As such, it moves a step forward from the measures purely based on the Standard Industrial Classification (SIC) or related classifications. As an application of our measure, we construct the index on 36,375 acquisition deals, the whole Dutch domestic acquisition market over the time span 1980-2005, with companies active in more than 200 industries at the 3-digit level. We study the flows of acquisitions among the macro-sectors defined by Eurostat according to the level of technology/ knowledge embedded. Our analysis shows that regardless of the considerable average level of relatedness inside each macro-sector, industries characterized by a high level of technology/knowledge intensity show a wider acquisition strategy when compared to low-tech industries. Also, companies operating in the financial sector proved to be less industry related in their target search*

Keywords: *industry relatedness; acquisitions; firm's diversification; firms' alliances*

JEL classification: G34; L60; L80

I. INTRODUCTION

INDUSTRY relatedness is an important concept in many contexts: acquisitions are an example in which such a context cannot be neglected. In acquisition framework, industry relatedness is defined as the degree to which the acquiring and the target firms are active in related markets, which implies that they rely on similar or complementary resources, knowledge bases, technologies, and products (Capron, 1999; Lim & Lee, 2016). Industry relatedness in target selection and the resulting corporate coherence are crucial aspects of the acquirer's strategy growth (Berger & Ofek, 1995; Bryce & Winter, 2009; Chatterjee & Wernerfelt, 1991; Coad & Guenther, 2013, 2014; Lien & Klein, 2009; Neffke & Henning, 2008; Piscitello, 2000; Rumelt, 1982; Teece, 1982). Previous research has investigated how industry relatedness between acquiring and target firms affects the likelihood of completing a deal (Lim & Lee, 2016); its profitability (Limmack & McGregor, 1995; Lubatkin, 1987); and the acquirers' innovative performance (Ahuja & Katila, 2001; Cassiman & Veugelers, 2006; Cloudt, Hagedoorn, Van Kranenburg, 2006; Keil, et al. 2008).

The aim of this work is to propose an operational instrument of industry relatedness that, first, relies on the observation of the actual combinations of industries and, second, accounts for the directionality of the relationship. We provide a more accurate measure of industry relatedness particularly specified for the acquisition framework, that can be easily transferred to other contexts where the complexity and the directionality of the relationship are important. To construct the index we start from the endogenous notion of proximity, introduced by Teece et al. (1994) and further elaborated by Bryce and Winter (2009), and we add directionality to the process. The importance of taking directionality into account is assessed in this work by showing the difference in the relatedness measure when comparing the acquirer-target to its opposite (target-acquirer) in the calculations.

As an application of our measure, we computed the index for the acquisition context considering the whole population of 36,375 domestic deals realized in The Netherlands between 1980 and 2005. The companies included in our study are active in more than 200 industries at 3 digit level. Coherently with previous literature, our results show that the selection of a target by an acquiring firm is not random (Boschma & Ellwanger, 2012; Bryce & Winter, 2009; Chatterjee & Wernerfelt, 1991). When breaking down by industry, we find that Dutch manufacturing companies have on average a more related

acquisition strategy than service companies. Industries characterized by a low level of technology show a wider acquisition strategy when compared to high-tech industries. Companies operating in the financial sector, typically less tied to synergies creation, are the most open in their target search. The directionality and the robustness of our index are supported by its comparison with its transpose version and with the relatedness measure proposed by (Neffke & Henning, 2013).

The strengths of the method we propose allow its implementation in a number of management/ economics fields, whereas the relatedness of the association between two entities is driven by a direction or a strategy. Our measure can be used as an independent variable or as a weight factor in spatial econometric analyses at the firm/sector level. Upon request, we supply the entire matrix of the relatedness industry (at 3-digit level) indexes for the acquisitions framework ready to use for those interested.

II. EXISTING MEASURES OF RELATEDNESS

Several measures have been proposed by scholars to measure how strongly related industries are to each other reliably. The first ones rely on SICs based on hierarchical nested structures in which each level is represented by a digit (see Berger & Ofek, 1995; Capron, 1999; Keil et al., 2008; Lim & Lee, 2016; Limmack & McGregor, 1995; Robins & Wiersema, 2003; Rumelt, 1982). However, though relatedness measures based on SICs are straightforward to compute, they lack an underlying relatedness scale. In fact, SICs typically reflect a broad logic of vertical structure and primary raw material, but leave unclear the conditions under which firms combine resources to create value and the significant strategic relationships among industries (Bryce & Winter, 2009; Lien & Klein, 2009; Neffke & Henning, 2013; Robins & Wiersema, 1995; Teece et al., 1994).

To overcome these shortcomings, some alternative approaches have been proposed. In the framework of knowledge-relatedness studies, Scherer (1982) observed the inter-industries R&D and technology flows to determine a measure of technology relatedness. Similarly, other researchers used firms' patents and their likelihood of being filed in multiple technology classes to map industry relatedness (Engelsman & van Raan, 1994; Jaffe, 1986, 1989). For the same purpose, similarities in upward and downward linkages in input-output matrices (Fan & Lang, 2000; Lemelin, 1982) or overlap in occupational categories employed by different industries (Farjoun, 1994) were used too.

More recently, several scholars have turned to co-occurrence analysis to assess relatedness (Breschi, Lissoni,

[Malerba, 2003](#); [Bryce & Winter, 2009](#); [Neffke & Henning, 2008](#); [Nesta & Saviotti, 2005](#); [Piscitello, 2000](#); [Teece et al., 1994](#)). This method, first proposed by Teece et al. (1994), stems from the survivor principle for which economic competition leads to the survival of only those units characterized by the most efficient mix of activities ([Alchian, 1950](#); [Friedman, 1953](#); [Lien & Klein, 2013](#)). Due to its proved ability to outperform SIC-based measures in predicting firms' diversification decisions ([Lien & Klein, 2009](#)), this methodology has been applied to a range of issues in strategic management, corporate finance, and industrial economics ([Bryce & Winter, 2009](#)). For instance, Nesta and Saviotti (2005) and Breschi et al. (2003) addressed the frequency with which two technology classes are jointly assigned to the same patent application as a proxy of the strength of their technological relatedness. Neffke and Henning developed a measure of relations between industries observing their product portfolios (2008) as well as a labor-flow based skill-relatedness measure (2013).

III. DATA AND SAMPLE

The data used in this study are gathered from the Dutch Business Register (ABR), elaborated by the Netherlands Central Bureau of Statistics (CBS). The ABR contains the entire population of firms registered for fiscal purposes in the Netherlands, providing demographic data: domestic employment data, a sector of activity, and dates and reason of entry and exit of a firm in/from the market (Cefis & Marsili 2012, 2015). We identified 36,375 domestic acquisitions completed in the Dutch market over the period 1980-2005. As both the acquiring and the target must be fiscally registered in The Netherlands to be tracked in the ABR, cross-border deals are not observed in this work. For each deal, we gathered the NACE industry code at the 3-digit level of both the acquirer and the target. Cases in which firms are active in multiple industries have been addressed by identification of the main affiliation.

TABLE 1
Breakdown of the sample by acquirers' and targets' industry.

Main Section	Acquirers		Targets	
	Obs.	%	Obs.	%
<i>High-tech Manufacturing</i>	229	0,63%	225	0,62%
<i>Medium-tech Manufacturing</i>	2549	7,01%	1615	4,44%
<i>Low-tech Manufacturing</i>	1031	2,83%	1578	4,34%
<i>Total manufacturing</i>	3809	10,47%	3418	9,40%
<i>Market Service ex Fin. intermediation</i>	21642	59,50%	22585	62,09%
<i>Financial Intermediation</i>	2856	7,85%	2736	7,52%
<i>Non-market Service</i>	4524	12,44%	4473	12,30%
<i>Total Service</i>	29022	79,79%	29794	81,91%
<i>Other</i>	3544	9,74%	3163	8,70%
<i>Total</i>	36375	100%	36375	100%

Table 1 presents a breakdown of the sample by the industry of both acquirers and targets. The two main macro-industries observed are manufacturing, involving 3,809 acquirers and 3,418 targets, and service, which involves 29,022 acquirers and 29,794 targets. Coherently with the Eurostat technology level regulation of the NACE classification, manufacturing and service are further classified as follows: according to the technology level (High, Medium, and Low-Tech) for the manufacturing class, and into Non-market service, Market service except financial intermediaries, and Financial intermediaries in the case of the service class. Furthermore, 3,544 acquirers and 3,163 targets are classified as Other.

IV. METHODOLOGY

A. Construction of the unidirectional index

This paper extends Teece et al. (1994) methodology to fit the acquisitions' framework. As we aim at taking the acquirer perspective in target selection, the directionality acquirer-target of the process is important. Consistently with corporate coherence research ([Piscitello, 2000](#); [Teece et al., 1994](#)), we expect that the acquirers' strategy in target search doesn't follow a random path. Our index relies on the following logic: if companies active in industry A very often acquire firms operating in sector B, these industries are highly related. Conversely, sectors rarely or never combined are unrelated. In order to operationalize the concept, we first define K as the total number of deals in the dataset (36,375); A as the sample of the acquired companies; and T as the sample of the targets. Let $B_{ia} = 1$ if acquirer firm a is active in industry i , and 0 otherwise; similarly, let $G_{jt} = 1$ if the target firm t is active in field j . Accordingly, the number of acquirers belonging to a specific industry i and the number of targets belonging to a specific industry j are $n_i = \sum B_{ia}$, and $MJ = \sum G_{jt}$, respectively. For each pair of acquirer (i) - target (j) industries the number of observed co-occurrences is counted in the corresponding cell o_{ij} of the co-occurrences matrix Ω as follows: $o_{ij} = \sum B_{ia}G_{jt}$. In our study, the co-occurrences matrix consists of $204 \times 204 = 41,616$ cells: the

whole set of combinations of the industries the acquirers (204 matrix's rows) and the targets (204 matrix's columns) belong to, defined at the 3-digit level of the European NACE classification. According to the acquirer perspective, Ω is asymmetrical that is, the cells o_{ij} and o_{ji} typically have different values. The cells $o_{ii} = \sum B_{ia} G_{it}$ constitute the diagonal of the co-occurrences matrix where the acquirer and the target are active in the same sector i .

The raw count of the numbers of observed co-occurrences cannot be directly taken as a measure of relatedness between two industrial sectors, because it is biased by the sample size and by the number of firms belonging to each sector since its spectrum $[0, \min(n_i, M_j)]$ is pair dependent. In fact, o_{ij} not only increases with the relatedness of i and j , but also with the size of n_i and/or m_j , however, does not straightforwardly allows the significance of the link. So, in order to obtain an unbiased index, we standardize o_{ij} adjusting for the value that would be expected under the hypothesis that the acquisition strategy is random. This test of randomness is performed, for each pair of industries, by comparing the empirically observed number of co-occurrences with the theoretical number estimated in the absence of any acquisition strategy, that is, when the co-occurrences are random. As a random benchmark, Teece et al. (1994) and Bryce and Winter (2009) propose the hypergeometric probability distribution of co-occurrences X_{ij} . Operationalizing the hypergeometric distribution, we obtain that the randomly occurring deals in which acquirers operating in sector i (of size n_i) buy a target belonging to sector j (of size m_j) is defined by:

$$P[X_{ij} = x] = \frac{\binom{n_i}{x} \binom{K - n_i}{m_j - x}}{\binom{K}{m_j}}, \quad (1)$$

$$x \leq \max\{n_i, m_j\}$$

The mean μ_{ij} (2) and variance σ_{ij}^2 (3) of X_{ij} are as below: (population K , number of acquirers belonging to sector i , n_i , and number of targets belonging to sector j , m_j):

$$\mu_{ij} = E(X_{ij}) = \frac{n_i m_j}{K} \quad (2)$$

$$\sigma_{ij}^2 = \mu_{ij} \left(\frac{K - n_i}{K} \right) \left(\frac{K - m_j}{K - 1} \right) \quad (3)$$

Applying the test of randomness to the acquisitions framework, two industries are highly related when the

actual number of joint occurrences o_{ij} observed between the activity field i of the acquirer and j of the target significantly exceeds the expected value μ_{ij} of the random co-occurrence X_{ij} . Conversely, when $o_{ij} < \mu_{ij}$ then industries i and j represent a complementary set of relatively underrepresented pairs. Hence, the relatedness index ρ_{ij} is defined standardizing the observed value of the co-occurrences using the mean (2) and the standard deviation (3) of the hypergeometric distribution as:

$$\rho_{ij} = \frac{o_{ij} - \mu_{ij}}{\sigma_{ij}} \quad (4)$$

which measures how many standard deviations away the observed values are from their expected values under the null hypothesis of randomness. Since large values of ρ are very unlikely under the null, their observation implies that some mechanisms are forcing the two fields to appear together so often, hence their large relatedness. To account for every expansion option the firm may face, the construction provides a score for any possible industry combination, including those not realized in the timeframe of our analysis and intra-sector deals, i.e., when both the acquirer and the target belong to the same industry.

B. Testing the hypothesis of randomness

Following Breschi et al. (2003), we test the statistical significance of the relation between each pair of industries by calculating, for each element ρ_{ij} , the associated p-value under the null hypothesis of random matching between industries.

TABLE 2
Test of Randomness.
Positive Cells

Acquirer's Industry	# pairs	Positive cells		
		#	# stat. sign.	% stat. sign.
High-tech Manufacturing	2244	95	72	75,79%
Medium-tech Manufacturing	9588	504	373	74,01%
Low-tech Manufacturing	10608	461	334	72,45%
Whole manufacturing	19992	932	675	72,42%
Market Service ex Fin. intermediation	13056	1144	648	56,64%
Financial Intermediation	1020	125	62	49,60%
Non-market Service	3876	211	128	60,66%
Whole Service	17952	1480	838	56,62%
Other	3672	243	167	68,72%
Total	41616	2645	1680	63,52%

Negative Cells

Acquirer's Industry	Negative cells		
	#	# stat. sign.	% stat. sign.
High-tech Manufacturing	2149	4	0,19%
Medium-tech Manufacturing	9084	118	1,30%
Low-tech Manufacturing	10147	172	1,70%
Whole manufacturing	19060	250	1,31%
Market Service ex Fin. intermediation	11912	1475	12,38%
Financial Intermediation	895	176	19,66%
Non-market Service	3665	371	10,12%
Whole Service	16472	2022	12,28%
Other	3429	218	6,36%
Total	38971	2490	6,39%

Table 2 reports the results of the test of randomness performed breaking down the sample by the acquirer's field of activity. For each industry category, the table first reports the number of possible pairs of industries. In the case of the complete sample, both the acquirer and the target can belong to 204 possible industries, allowing for 204x204 feasible pairs. Then, the columns 2-4 report, respectively, the number of pairs resulting in a positive level of relatedness ρ and the number and percentage of those that are statistically significant (at a 10% level). A similar presentation is offered in columns 5-7 for the pairs with a negative value of relatedness.

Overall, results show that the percentage of pairs with significant non-random (positive or negative) value of industry relatedness is above 70%, independently on the industry of the acquirer. In other words, some industries are more (less) frequently related that it would happen under the null hypothesis, allowing us to reject the null hypothesis of randomness. The majority of statistically significant values are positive (considering, e.g., the whole sample, about 63% of the dyads with positive index are statistically significant, while only 6.4% with negative index is statistically significant), even though the number of feasible pairs resulting in negative index values strongly overcomes the number of positive cases. This can be explained by the fact that several combinations never realize in the real market. For instance, consider the whole sample again, over the total of 41,616 possible pairs, 37,073 actually never combine.

Table 3 reports the descriptive statistics of the relatedness index ρ_{ij} breakdown by the industry of the acquirer. The last column reports the ranking of the industrial classes by relatedness level (1 being the highest, 6 the lowest).

Comparing the different macro sectors, we see that the service sector has on average a more diversified acquisition strategy than the manufacturing industry (mean $\rho_{ij, service} = 2.25$; mean $\rho_{ij, manufacturing} = 10.28$). Acquirers active in the

financial intermediation category are the broadest in acquisition search (mean $\rho_{ij} = 0.75$). Financial companies are in fact characterized by an acquisition pattern that is unique to this sector. Institutions such as Private Equity and Venture Capital firms, for instance, base their search on the purpose of getting returns to the investment through successful exit strategies rather than exploiting synergies (e.g. [Achleitner, et al., 2014](#); [Cressy, Munari, & Malipiero, 2007](#); [Kaplan & Stromberg, 2009](#); [Rigamonti, et al., 2016](#)).

On the one hand, manufacturing acquirers tend to stick on a more related acquisition strategy, and the average level of relatedness in target search increases moving from low ($\rho_{ij} = 9.99$) to medium ($\rho_{ij} = 10.02$) to high ($\rho_{ij} = 13.81$) technology level. In fact, although technological diversification allows innovative companies to avoid technological lock-in ([Suzuki & Kodama, 2004](#)) and constitutes an important competitive advantage in dynamic innovation environments ([Ahuja & Katila, 2001](#); [Gambardella & Torrisi, 1998](#); [Modrego et al., 2015](#)), companies still need enough absorptive capacity in order to understand and integrate new procedures ([Cefis & Marsili, 2015](#); [Laursen & Salter, 2006](#); [Miller, Fern, & Cardinal, 2007](#)).

TABLE 3
Descriptive statistics of ρ_{ij} and the ranking of the industrial classes by relatedness level.

Acquirer's Industry	Mean	S.D.	Min	Max	Rank
High-tech Manufacturing	13,81	23,45	-1,53	108,9	6
Medium-tech Manufacturing	10,02	23,71	-3,19	190,7	5
Low-tech Manufacturing	9,99	23,45	-3,53	134	4
Whole manufacturing	10,28	23,51	-3,53	190,7	
Market Service ex Fin.	2,14	16,31	-10,16	162,1	2
Financial Intermediation	0,75	10,6	-6,46	99,37	1
Non-market Service	3,45	23,19	-9,7	175,3	3
Whole Service	2,25	17,34	-10,16	175,3	
Other	2,33	19,05	-7,36	159,2	
Total	4,31	19,77	-10,16	190,7	

V. ROBUSTNESS CHECK

We performed several robustness checks. First, the hypothesis of randomness has been tested as described in Section IV.B clustering the sample by the acquirer's experience in acquisitions, i.e., by grouping the acquirers by the number of acquisitions performed at the event time since foundation. Specifically, we tested several clusters. We started by selecting the companies that did not have any acquisition experience before the event, and then we proceeded the analysis to those companies that acquired up to two targets, up to three targets and so on until the maximum number of multiple acquisitions observed in our sample. The results (available on request) allow the rejection of the hypothesis of randomness for each of the

clusters, supporting the previous findings.

Second, to show the effect of implementing a unidirectional measure, we constructed the index taking the opposite perspective, i.e., a relatedness index unidirectional from the target to the acquirer. This index is based on the co-occurrences matrix Ω^T , the transpose of matrix Ω defined in section 4.1. We do not display the full matrix of relatedness index ρ_{ij}^T for the sake of brevity, however, due to the asymmetric nature of the matrix itself, the value of the index changes with its direction for each pair of industries. The panel, an of Table 4, shows the descriptive statistics of the transpose index ρ_{ij}^T breakdown by industry.

Comparing these results with those displayed in Table 3, it is possible to see that the magnitude of the index changes between the original ρ_{ij} and its reverse direction for each industry. For example, results show that the likelihood that a high-tech acquirer is interested in unrelated targets is lower than the likelihood that a high-tech target attracts unrelated acquirers. As such, this comparison between the index and its transpose prove that the directedness of the relatedness network matters.

TABLE 4
Robustness checks: ρ_{ij}^T the transposed version of the index, and $\overline{R_{ij}}$ the relatedness measure proposed by Neffke et al. (2013, 2017).

Panel a.

Acquirer's Industry	Index $\rho(ij)^T$ (Transpose)				
	Mean	S.D.	Min	Max	Rank
High-tech Manufacturing	7,46	21,66	-2,03	108,87	5
Medium-tech Manufacturing	6,54	23,08	-3,73	23,08	4
Low-tech Manufacturing	7,58	23,72	-3,97	23,72	6
Whole manufacturing	6,91	22,97	-3,97	22,97	
Market Service ex Fin.	2,16	15,55	-9,75	15,55	2
Financial Intermediation	0,75	9,63	-7,11	9,64	1
Non-market Service	5,18	25,41	-10,16	25,41	3
Whole Service	2,43	16,83	-10,16	16,83	
Other	5,23	17,86	-3,28	17,86	
Total	3,67	18,81	-10,16	18,81	

Panel b.

Acquirer's Industry	Relatedness $R(ij)$				
	Mean	S.D.	Min	Max	Rank
High-tech Manufacturing	0,65	0,37	-0,53	0,99	6
Medium-tech Manufacturing	0,48	0,47	-0,81	0,99	5
Low-tech Manufacturing	0,46	0,51	-0,85	0,99	4
Whole manufacturing	0,48	0,48	-0,84	0,99	
Market Service ex Fin.	0,03	0,54	-0,97	0,99	2
Financial Intermediation	-0,04	0,46	-0,95	0,95	1
Non-market Service	0,08	0,57	-0,96	0,99	3
Whole Service	0,03	0,53	-0,97	0,99	
Other	0,19	0,56	-0,99	0,99	
Total	0,16	0,55	-0,99	0,99	

by Teece et al. (1994) has some drawbacks. Specifically, the degree of relatedness between two individual industries might be biased by the size of the industries involved in the calculations. In other words, as large industries represent large sample sizes, any distance between ρ_{ij} and μ_{ij} in equation (4) likely becomes significant because the denominator σ_{ij} is small. For this reason, we use a comparable methodology to check the validity of our index. Specifically, we test our index against the measure of relatedness R_{ij} proposed in (Neffke & Henning, 2013; Neffke, Otto, & Weyh, 2017) which is directional and not affected by size issue but does not straightforwardly allows the significance of the link. Applying the terminology used in the present paper, the measure of Neffke and Henning (2013) is calculated as: $R_{ij} = \rho_{ij} / \mu_{ij}$, where, similarly to the logic used in our index, values of R_{ij} from 1 to ∞ indicate levels of relatedness above the benchmark; values of R_{ij} between 0 and 1 indicate levels of relatedness below the benchmark. Applying the correction suggested in Neffke et al. (2017) R_{ij} can then be mapped onto the interval [-1 ; 1] symmetrically with respect to zero as:

$$\overline{R_{ij}} = \frac{R_{ij} - 1}{R_{ij} + 1} \quad (5)$$

Descriptive statistics of $\overline{R_{ij}}$ breakdown by industry are shown in Panel b of Table 4. The ranking of the industrial sectors obtained by observing the mean values of $\overline{R_{ij}}$ confirms the validity of our index.

VI. CONCLUSIONS

This paper proposes a unidirectional index to measure the industry relatedness. We applied the methodology to the acquisitions framework as it well exemplifies the importance of the directionality of a relationship between an origin firm and a target firm. The proposed index relies on the framework of observed co-occurrence and survival principle proposed by Teece et al., 1994, while also accounting for the directionality of the relationship among firms. As such, it represents a useful operational instrument to capture industry relatedness in micro (firm) level studies as well as to investigate macro flows in phenomena where the directionality of the relationship is essential.

We applied the index to analyze the Dutch acquisition market. Through the analysis of a sample of 36,375 acquisitions by companies active in more than 200 3-digits NACE industries, we show that the selection of a target by an acquiring firm occurs according to non-random strategies. We find that although a considerable degree of relatedness is observed across the market, the picture varies

Third, we acknowledge that the methodology proposed

when considering macro-industries with different technological intensity. In fact, while acquirers active in manufacturing industries are more restricted in their target search, others show a more diversified acquisition strategy, in particular, financial intermediaries. This results and the validity of the proposed measure has been confirmed by checking our index against its transpose version and the relatedness measure suggested by Neffke and Henning (2013).

We believe that the potential of this index is its applicability. First, beyond acquisitions, our measure can be applied to all the frameworks where the directionality of the relationship between pairs of entities is crucial and where the survivor principle holds. Examples could include studies on partners' proximity in business development activities, such as collaborations, alliances, or business networks. Second, our measure can have different implementations in empirical research strategies: it can be used as an independent variable to proxies the industry relatedness in econometric models at the firm/sector level, or as the weighting factors in matrices for spatial econometrics models.

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