Interdisciplinarity and Impact: Distinct Effects of Variety, Balance, and Disparity

Jian Wang[1], Bart Thijs[1] and Wolfgang Glänzel[1]

{Jian.Wang, Bart.Thijs, Wolfgang.Glanzel}@kuleuven.be
[1] KU Leuven (Belgium)

Abstract

Interdisciplinary research is increasingly recognized as the solution to today's challenging scientific and societal problems, but the relationship between interdisciplinary research and scientific impact is still unclear. This paper studies the relationship between interdisciplinarity and citations at the paper level. Different from previous literature compositing various aspects of interdisciplinarity into a single indicator, this paper uses factor analysis to uncover distinct aspects of interdisciplinarity and investigates their independent dynamics with scientific impact. Three uncovered factors correspond to variety, balance, and disparity. Subsequently, we estimate Poisson models with journal fixed effects and robust standard errors to investigate the relationship between these three factor and citations. We find that the number of citations (1) increase at an increasing rate with variety, (2) decrease with balance, and (3) increase at a decreasing rate with disparity. These findings have important implications for interdisciplinarity research and science policy.

Conference Topic

Science policy and research assessment

Introduction

Interdisciplinary research has been increasingly viewed as the remedy for the challenging contemporary scientific and societal problems. As important ideas often transcend the scope of a single discipline, interdisciplinary research is the key to accelerate scientific discoveries and solve societal problems. Given the normative interest in and the policy push for interdisciplinary research, it's important to empirically investigate the consequences of interdisciplinary research. Bibliometric studies have explored the relationship between interdisciplinary research and citation impact, but findings are mixed. For example, Steele and Stier (2000) found a positive effect of interdisciplinarity on citation impact for environmental sciences papers, where interdisciplinarity was measured as the disciplinary diversity of the cited references. Rinia, van Leeuwen, van Vuren, and van Raan (2001) studied physics programs in the Netherlands and operationalized interdisciplinarity as the ratio of non-physics publications. They found significantly negative correlations between interdisciplinarity and non-normalized citation-based metrics, but correlations became insignificant when field-normalization took place. Levitt and Thelwall (2008) found that interdisciplinary papers received fewer citations in life and physical sciences but not in social sciences, and interdisciplinary papers were defined as papers published in journals assigned to multiple subject categories. Larivière and Gingras (2010) analyzed all Web of Science (WoS) articles published in 2000, measured interdisciplinarity as the percentage of its cited references to other disciplines, and found an inverted *U*-shaped relationship between interdisciplinarity and citations.

One possible explanation for these conflicting results pertains to their different choices of the interdisciplinarity measure. On the one hand, a number of interdisciplinarity indicators have been proposed, at various levels (e.g., paper, journal, institution, and fields) and using various bilometric information (e.g., disciplinary memberships of authors, published journals, or cited references). On the other hand, the concept of interdisciplinarity remains an abstract and complex one (Wagner et al., 2011). One useful conceptualization is to view interdisciplinarity as the diversity of disciplines invoked in the research (Porter & Rafols, 2009; Stirling, 1998, 2007). Furthermore, diversity has three distinct components (Stirling, 2007, p. 709):

> *Variety is the number of categories into which system elements are apportioned. It is the answer to the question: 'how many types of thing do we have?'*
>
> *Balance is a function of the pattern of apportionment of elements across categories. It is the answer to the question: 'how much of each type of thing do we have?'*
>
> *Disparity refers to the manner and degree in which the elements may be distinguished. It is the answer to the question: 'how different from each other are the types of thing that we have?'*

Many studies have devoted to compositing all aspects of interdisciplinarity into one single indicator. However, this paper adopts an opposite approach: we decompose different aspects of interdisciplinarity and explore their unique relationships with citation impact, at the individual paper level. Given that interdisciplinarity is an abstract and multidimensional concept, there might not be a straightforward answer to the question of whether interdisciplinary research draws higher impact. Instead, we should ask the question in another way: what kinds of interdisciplinarity have positive/negative relationships with citation impact? In addition, nuanced understanding of the divergent dynamics underlying different aspects of interdisciplinarity is also important for informing interdisciplinary research and science policy.

Data and methods

We analyzed all the journal articles published in 2001 indexed in the Thomson Reuters Web of Science Core Collection (WoS). Only articles were analyzed, while all other document types such as reviews and letters were excluded. The year 2001 was chosen so that studied papers could have a sufficiently long period to accumulate their citations (Wang, 2013).

Interdisciplinarity measures

Following previous literature, we constructed interdisciplinarity measures for each individual articles based on the disciplinary profile of its cited references, since referencing to prior literature in various disciplines indicates drawing and integrating knowledge pieces from these disciplines. Specifically, we constructed interdisciplinarity measures based on the WoS subject categories (SCs) referenced by each article. Interdisciplinarity measures constructed in this paper are listed in Table 1, which have been commonly used in the literature (Leydesdorff & Rafols, 2011; Rafols et al., 2012; Stirling, 2007). Because the last two interdisciplinarity measures cannot be constructed if the focal article references fewer than two subject categories, we excluded these articles from the analysis. Nevertheless, regressions using the whole dataset for the other measures yielded consistent results. In total, our data have 646,669 papers.

Factor analysis

We used factor analysis to uncover components underlying these interdisciplinarity measures. The first step was to determine the number of factors to retain. A classic approach is Kaiser's eigenvalue greater than one rule (Kaiser, 1960). The idea is that the retained factor should explain more variance than the original standardized variables. Horn's parallel analysis

Table 1. Interdisciplinarity measures.

Measure	*Description*
Ratio of references to other subject categories	
Number of referenced subject categories	n
1 – Gini	$$1-\frac{\sum(2i-n-1)x_i}{n\sum x_i}$$ where i is the index, x_i is the number of references to the i-th subject category, and subject categories are sorted by x_i in non-decreasing order.
Simpson index	$$1-\sum p_i{}^2$$ where $p_i = x_i/X$, and $X = \sum x_i$
Shannon entropy	$$-\sum p_i log\ (p_i)$$
Average dissimilarity between referenced subject categories	$$\frac{1}{n(n-1)}\sum_{i\neq j} d_{ij}$$ where d_{ij} is the dissimilarity between subject category i and j. Specifically, $d_{ij} = 1 - s_{ij}$, where s_{ij} is the cosine similarity between subject category i and j based on their co-citation matrix.
Rao-Stirling diversity	$$\sum_{i\neq j} p_i p_j d_{ij}$$

modified Kaiser's rule, where the criterion for each eigenvalue is different and also superior to one, and these criteria are obtained from a Monte-Carlo simulation (Horn, 1965). Cattell's scree test provided a graphical strategy: plotting the eigenvalues against the component numbers and searching for the elbow point (Cattell, 1966). However it does not yield a definitive number of factors to retain, which still relies on subjective judgments of the researcher. Recently, Raiche, Walls, Magis, Riopel, and Blais (2013) developed numerical solutions for Cattell's scree test: (1) the optimal coordinate solution for the location of the scree and (2) the acceleration factor solution for the location of the elbow. We implemented all these methods to determine the number of factors. After determining the number of factors to retain, we extracted these factors using the varimax rotated principal components method. In addition, the number of referenced subject categories is highly skewed, so its nature logarithm was used in the factor analysis.

Regression analysis

To study the relationship between interdisciplinarity and citation impact at the article level, we ran regressions, using the number of long-term citations (in a 13-year time window from 2001 to the end of 2013) as the dependent variable and the interdisciplinarity measures and extracted factors as explanatory variables.

For all our regressions, we incorporated journal fixed effects to control for (1) unobserved topic/subfield heterogeneities at a very refined level and (2) journal reputation effects (Judge et al., 2007). Therefore, we estimated the within-journal effects, in other words, we were evaluating the association between interdisciplinarity and citations among papers published in the same journal. In addition, the following variables were incorporated as controls: the number of authors, the number of countries, the number of pages, and the number of references. The numbers of authors, pages, and references are skewed so that their natural logarithms were used in regression analyses. The number of countries is still highly skewed after logarithm transformation, so we created a dummy variable, international: 1 if the paper has authors from more than one country, and 0 otherwise. In our sample, about 19% of the papers are internationally coauthored.

Because citation counts are over-dispersed count variables, we used Poisson regression with robust standard errors, following previous literature (Hall & Ziedonis, 2001; Hottenrott & Lopes-Bento, In Press; Somaya, Williamson, & Zhang, 2007). An alternative is the negative binomial model. However, because the Poisson model is in the linear exponential class, Gourieroux, Monfort, and Trognon (1984) have shown that the Poisson estimator and the robust standard errors are consistent so long as the mean is correctly specified even under misspecification of the distribution, but the negative binomial estimator is inconsistent if the true underlying distribution is not negative binomial. Therefore, we adopted the Poisson model with robust standard errors in our empirical analysis. Furthermore, we incorporated journal fixed effects. Such fixed effects Poisson models can be fitted by conditioning out the individual fixed effects (Hausman, Hall, & Griliches, 1984).

Results

Decomposing interdisciplinarity

We used the following variables in the factor analysis: log number of referenced subject categories, ratio of references to other subject categories, 1 – Gini, Simpson index, Shannon entropy, average dissimilarity between referenced subject categories, and Rao-Stirling diversity. The first three eigenvalues are greater than 1, so 3 factors should be retained according to Kaiser's rule. Horn's parallel analysis also suggests 3 factors. Raiche's nongraphic solutions for Cattell's scree test lead to conflicting conclusions: the optimal coordinate approach suggests 3 factors, while the acceleration factor approach suggests 1 factor to retain. Considering (1) the consensus between the classic Kaiser's rule and Horn's parallel analysis, (2) the divergence in this recent nongraphic solution for Cattell's scree test, and (3) that the optimal coordinate solution actually agrees with the more conventional approaches. We decided to retain 3 factors. Subsequently, we extracted 3 factors using the varimax rotated principal components method, and the cumulative proportion variance explained is 0.89. Factor loadings are reported in Table 2. Simpson index and Shannon entropy have the highest loading on the first factor, which reflects the variety aspect of disciplinary diversity. 1 – Gini has the highest loading on the second factor, which reflects balance, and the average dissimilarity between referenced subject categories has the highest loading on the third factor, which reflects disparity. The results are also in line with Harrison and Klein (2007) that Simpson index and Shannon entropy reflect more on variety, while Gini reflects more on unbalance.

Table 2. Factor loading.

	Factor 1	*Factor 2*	*Factor 3*
ln(referenced SCs)	0.78	-0.59	0.15
Ratio oth-disc refs	0.67	0.35	-0.17
1 – Gini	-0.07	0.94	0.05
Simpson	0.93	-0.11	0.18
Shannon	0.91	-0.32	0.18
Avg dissimilarity	0.09	0.00	0.95
Rao-Stirling	0.77	0.04	0.59

Data sourced from Thomson Reuters Web of Science Core Collection.

Interdisciplinarity and impact

We first estimated the fixed effects Poisson models using the citation counts as the dependent variable and original interdisciplinarity measures as the independent variables (Fig. 1A, regression table not reported). The divergent results suggest that the low consensus in previous literature regarding the relationship between interdisciplinarity and citation impact may be partially explained by their different choice of the interdisciplinarity measures.

Table 3 reports fixed effects Poisson models using the extracted interdisciplinarity factors as independent variables. Variety, balance, and disparity are the three extracted factors, and they follow the standard normal distribution with mean equals to 0 and standard deviation equals to 1. Holding that the papers are published in the same journal, with the same number of authors, pages and references, and have the same status in terms of whether being internationally coauthored, the expected number of citations increases by 1.48% as variety increases by 1 standard deviation (column 1), decreases by 2.45% as balance increases by 1 standard deviation (column 3), and increases by 5.77% as disparity increases by 1 standard deviation. Squared terms are subsequently added to test the non-linearity in these relationships. On the one hand, the square terms of variety and disparity are significant, suggesting nonlinear relationships. On the other hand, the squared term of balance is insignificant, suggesting a simply linear relationship. Fig. 1B plots the estimated number of citations with variety, balance, and disparity, based on column 2, 4, and 6 in Table 3, respectively. Again, for these estimations, we fix journal fixed effect at 0, international at 0, and all other variables at their mean.

We observe that long-term citations increase at an increasing rate with variety, which is in line with the information processing perspective that cognitive variety is very important for creative and innovative work (Lee, Walsh, & Wang, In Press; Page, 2007; Simonton, 2003). For interdisciplinary research, integrating knowledge from more disciplines contributes to potentially more broadly useful outcomes.

We also observe a negative relationship between balance and citation impact, which is also in line with Uzzi, Mukherjee, Stringer, and Jones (2013) that a paper with both higher novelty and conventionality are more likely to be a top cited paper. In other words, a paper is more likely to be top cited if it is embedded at the core of a discipline (drawing most of its prior knowledge/references from one discipline) while at the same time borrows some knowledge from some remote disciplines. However, the reason for this negative association between long-term citations and balance is still unclear. On the one hand, it could be that interdisciplinary research driving evenly by different disciplinary logics is more likely to fail in integrating these logics into something useful. Therefore, having one disciplinary core and simultaneously borrowing knowledge from other disciplines is a more effective research strategy, compared with drawing knowledge evenly from multiple disciplines. On the other hand, it could be that the current science system is biases against balanced interdisciplinary research. There are anecdotes that balanced interdisciplinary research which truly transcend disciplinary boundaries is difficult to evaluate and more likely to be unnoticed, simply because most scientists are trained within a discipline and unable to realize its value, although such balanced interdisciplinary research is very novel and broadly useful.

In addition, we observe that the number of citations increases with disparity but at a decreasing rate. This is in line with the combinatorial novelty literature that combining more remote disciplines is more novel than combining neighboring disciplines (Lee et al., In Press; Uzzi et al., 2013). Furthermore, there is a rather complex dynamics between novelty and impact. On the one hand, novelty is important for generating impact. On the other hand, a highly novel paper might not be useful or helpful for other scientists to further build on it, and therefore would fail to generate high impact (Latour & Woolgar, 1986; Merton, 1973; Whitley, 2000). We do observe that that the marginal return from disparity is decreasing. It's possible that the effect of disparity on long-term citations might turn into a negative one after certain point, but this threshold is about six standard deviations above the mean, which is beyond the maximum disparity value in our data.

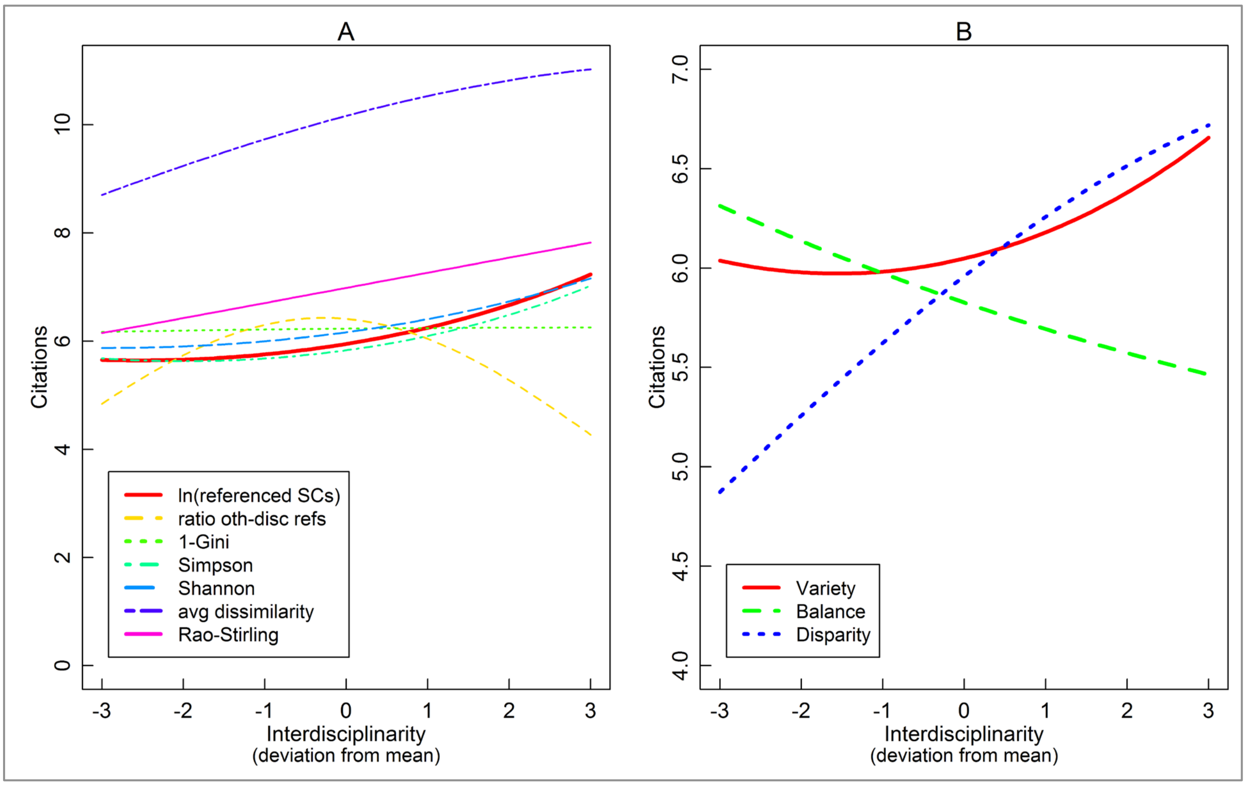

Figure 1. Interdisciplinarity and citations. Data sourced from Thomson Reuters Web of Science Core Collection.

Conclusions

This paper studies three different aspects of interdisciplinarity and investigates their distinct relationships with citation impact. The factor analysis extracts three main factors underlying various interdisciplinarity measures, and these three factors correspond to variety, balance, and disparity. Regression analysis further uncovers their different relationships with long-term citation impact: citations (1) increase at an increasing rate with variety, (2) decrease with balance, and (3) increase at a decreasing rate with disparity.

This paper contributes to future interdisciplinarity research and science policy. First, we advocate the idea of using different interdisciplinarity measures in different contexts. This paper demonstrates that various interdisciplinarity measures bear non-identical relationships with citation impact. Interdisciplinarity is an abstract and multidimensional concept, and different aspects of interdisciplinarity may (1) respond to certain individual, team, or institutional factors in completely different ways, and (2) have unique consequences in terms of usefulness or impact. Furthermore, various theories which might shed light on interdisciplinarity research have their own unique focuses. For example, the information processing perspective focuses on cognitive variety, while the combinatorial novelty literature emphasizes disparity. Therefore, it's important to choose a suitable interdisciplinarity measure consistent with the invoked theory and focal research question.

Table 3. Fixed effects Poisson models: interdisciplinarity and long-term impact (*N* = 646223).

	Citations							
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
ln(authors)	0.1588***	0.1586***	0.1600***	0.1600***	0.1590***	0.1586***	0.1578***	0.1575***
	(0.0105)	(0.0105)	(0.0106)	(0.0106)	(0.0110)	(0.0110)	(0.0107)	(0.0107)
International	-0.0009	-0.0008	-0.0013	-0.0013	-0.0025	-0.0025	-0.0023	-0.0022
	(0.0130)	(0.0130)	(0.0130)	(0.0130)	(0.0135)	(0.0135)	(0.0133)	(0.0133)
ln(pages)	0.4054***	0.4055***	0.4022***	0.4019***	0.3958***	0.3963***	0.3965***	0.3965***
	(0.0295)	(0.0295)	(0.0295)	(0.0294)	(0.0301)	(0.0302)	(0.0300)	(0.0300)
ln(refs)	0.3021***	0.3013***	0.2868***	0.2871***	0.3056***	0.3045***	0.2855***	0.2836***
	(0.0078)	(0.0077)	(0.0105)	(0.0105)	(0.0082)	(0.0083)	(0.0118)	(0.0119)
Variety	0.0148*	0.0162*					0.0137^{+}	0.0154^{+}
	(0.0061)	(0.0064)					(0.0078)	(0.0083)
Variety^2		0.0052*						0.0044^{+}
		(0.0026)						(0.0026)
Balance			-0.0245**	-0.0241**			-0.0194^{+}	-0.0194^{+}
			(0.0074)	(0.0073)			(0.0106)	(0.0108)
Balance^2				0.0009				0.0021
				(0.0033)				(0.0030)
Disparity					0.0577***	0.0535***	0.0528***	0.0488***
					(0.0075)	(0.0074)	(0.0088)	(0.0087)
Disparity^2						-0.0045^{+}		-0.0036
						(0.0025)		(0.0025)
Journal fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Log pseudolikelihood	-8642990	-8642683	-8642595	-8642588	-8629711	-8629503	-8628738	-8628365
χ^2	2946***	2957***	2967***	2961***	4450***	4438***	4552***	4807***

Cluster-robust standard errors in parentheses.
*** p<.001, ** p<.01, * p<.05, $^{+}$ p<.10.
Data sourced from Thomson Reuters Web of Science Core Collection.

Second, this paper suggests a more refined policy agenda for encouraging interdisciplinary research. This paper pushes forward the research on the relationship between interdisciplinarity and scientific impact: from a dichotomous question of whether interdisciplinary research draws higher impact towards a more complicated question about differentiated dynamics underlying different aspects of interdisciplinarity. Answers to this more complicated question is also important for more effective science policies. As science increasingly deals with boundary-spanning problems, various policy and funding initiatives have been developed to encourage interdisciplinary research, such as the US National Science Foundation (NSF) solicited interdisciplinary programs, the US National Institutes of Health (NIH) common fund's interdisciplinary research program, European Research Council (ERC) synergy grants, and UK Research Councils' cross-council funding agreement. However, interdisciplinarity is an abstract and multidimensional concept, and nuanced understanding of these different dimensions and their consequences are important for effective policies. Specifically, the positive relationship between variety and citation impact demonstrates the benefits of cognitive variety for creative work. Therefore, policy and funding initiatives can encourage research across more disciplinary boundaries and integrating knowledge from more disciplines. Furthermore, the positive relationship between disparity and citation impact also suggests potential improvements from encouraging interdisciplinary research across more remotely connected disciplines. However, since the positive marginal effect is decreasing, the policy might not want to push too far. It's possible that disparity effect on citations might turn into a negative one when the disparity is too high, that is, integrating disciplines too far apart may fail to find a common ground to produce something useful. In addition, the negative relationship between balance and citation impact may suggest that the most effective interdisciplinary research strategy in terms of generating impact is to have one disciplinary core and simultaneously borrow knowledge from some other disciplines, instead of drawing knowledge evenly from multiple disciplines without a disciplinary core. It's possible that research driving evenly by different disciplinary logics fails to integrate these logics into something useful. On the other hand, this might also suggest that balanced interdisciplinary research is biased against in the current discipline-based science system, in which scientists are mostly trained within a single discipline and therefore fail to realize the value of balanced interdisciplinary work which truly transcends interdisciplinary bounties. However, further research is required to better understand this problem. Specifically, to claim the bias against balanced interdisciplinary research, we need to estimate the unbiased should-be scientific impact first and then compare it with the observed citations. To recommend policies encouraging unbalanced instead of balanced interdisciplinary research, we would also need to test the usefulness or value of the papers directly, instead of only examining citation counts.

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