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Do Clusters Encourage Innovation? A Meta-analysis

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Abstract

This article carries out a meta-analysis on empirical studies addressing cluster–innovation relationships since the 1980s. The results show that (1) clusters have positive effects on innovation; (2) different studies demonstrate heterogeneity in the estimated effect sizes; (3) several moderators are shaping the cluster–innovation relationship, for example, in what industries the cluster specializes, in which geographical region the cluster is located, and so on. This article reveals the cluster–innovation relationships are state-contingent and provides guidance on evaluating whether a cluster strategy can encourage innovation in a specific region. For example, the regression result indicates initiating a manufacturing cluster in a US region is expected to bring about fifteen more patents every year.

Keywords

cluster, innovation, meta-analysis

Introduction

Recent decades have witnessed a new wave of interests in clusters from researchers and policy makers, and supporting clusters have become a prevalent local strategy in promoting economic development (M. E. Porter 1990; P. R. Krugman 1991; M. Feldman 2000; Storper and Scott 1995). Clusters are claimed to have positive effects on innovation, productivity, and resilience (Baptista 1998; Folta, Cooper, and Baik 2006; Treado and Giarratani 2008). This article addresses clusters' effects on innovation. It focuses on innovation for two major reasons. First, one important outcome of clusters is promoting innovative activities because clusters can foster the spillover of the elusive knowledge that is critical to innovation (M. P. Feldman 1994; Audretsch and Feldman 1996). Practically, some clusters do promote innovation and make the local economy prosperous, such as the Silicon Valley. Second, in modern economic growth theories, innovation is an important driving force of long-term economic success (Grossman and Helpman 1990; Aghion, Harris, and Vickers 1997; Freeman and Soete 1997). As a result, firms, regions, and countries all try to improve their capacities of innovation in order to achieve better economic performances (Calantone, Cavusgil, and Zhao 2002; Morgan 2007; Mairesse and Mohnen 2001). Thus, understanding clusters' effects on innovation can yield important insights into the issues of regional economic development and provide policy implications to local authorities.

To date, our knowledge of clusters' effects on innovation is mixed. Theoretically, clusters may encourage innovation due to knowledge spillover effects but may also jeopardize innovation due to "lock-in" effects (Cooke, Uranga, and Etxebarria 1997; Boschma 2005). Many empirical studies have investigated the relationship between clusters and innovation with data from various countries and time periods, but the results are inconsistent (Baptista and Swann 1998; Beaudry and Breschi 2003). Mixed results largely prohibit us from reaching any general conclusions. Meta-analysis is suggested as a meaningful way of combining empirical studies with contradicting results (Rosenthal 1991). Since individual studies inevitably suffer from problems such as measurement artifacts,[1] limited research range (relatively narrow geographical regions and time frames), and small sample size, combining and contrasting results from multiple studies are necessary for the aim of reaching powerful and robust general conclusions (Glass 1976). Yet to date little work like that has been done on the topic of clusters and innovation except the noteworthy paper of de Groot, Poot, and Smit (2010).

This article provides a meta-analysis of relevant empirical studies on the relationship of clusters and innovation since the 1980s. It differs from de Groot, Poot, and Smit (2010) in two aspects. First, de Groot, Poot, and Smit focus on the regional level effects, while this article pays equal attention to the regional-level and the firm-level effects. Moreover, this article explicitly compares the results from firm-level, industry-level, and regional-level studies, providing us additional knowledge about whether clusters' effects on innovation are mostly

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captured by the individual firms, kept in the industry, or absorbed by the region. Second, de Groot, Poot, and Smit include studies with dependent variables varying from employment growth, productivity growth to innovation. Therefore, their research question is in fact much broader than that of this article. But large variations in the dependent variables prohibit a clear interpretation of the results and make the calculation of an average effect size inapplicable.[2] This article restricts its concern to clusters' effects on innovation, and papers that do not have an innovation-related dependent variable are excluded. By doing so, this article is able to calculate a relatively meaningful average effect size and arrives at results that are easier to interpret,[3] at the expense of a smaller sample size.[4] Admittedly, variations in the measurements of "cluster" and "innovation" still exist in the samples of this article, which could make the estimation of the average effect size less precise, but it is still possible and meaningful to estimate the average effect size, especially when I employ the random effects model in which the heterogeneity is taken into consideration. Such an average effect size, if turns out to be significantly positive, means that "cluster" in general is positively related to "innovation"; however, the sampling studies define and measure the two variables. Moreover, by employing the mixed effects model, this article explicitly explores whether and by what magnitude those variations in measurements would result to differences in the estimated effect sizes. Those interesting results cannot be obtained if I restrict my samples to exactly the same measurement. I choose to attempt at a more general conclusion, at the expense of the precision of the estimation.[5] Other potential outcomes of clusters, such as productivities and employment, are also important factors in the considerations of pursuing a cluster strategy, but studying them are beyond the scope of this article.

This article attempts to address three questions. (1) What are the general conclusions of clusters' influences on innovation from previous studies? (2) Are previous studies homogeneous or heterogeneous in their estimated correlations between clusters and innovation? (3) If they are heterogeneous, what variables may serve as moderators? Namely, what variables may influence the direction and magnitude of clusters' effects on innovation?

Using the fixed effects and random effects model, this article reveals that generally speaking, clusters have statistically positive effects on innovation. Using Cochrane's Q statistics and I^2 statistics, significant heterogeneity is found across individual studies, suggesting moderators may be at work in shaping the cluster–innovation relationship. Using mixed effects models, potential moderators such as how is cluster measured, which industry is primary in the cluster, firm size, and so on, are identified. This article provides useful guidance for local authorities in the following ways. First, generally speaking, initiating a cluster strategy to promote innovation is promising. Second, for a specific cluster, the direction and magnitude of the relationship cannot be determined without considering a handful of important moderators, such as cluster characteristics (e.g., does it have high concentration/localization?), industries, and whether we care about the firm-level, industry-level, or regional-level innovation performances. Third, based on the results of this article and relevant local data, we can form an expectation of the direction and magnitude of a specific cluster's effects on innovation. The cluster can either be an existing one or a hypothetical one.

This article proceeds as follows. The second section summarizes related studies in a qualitative way, highlighting the theoretical debate and inconsistent empirical results. The third section describes the data and the methodology. The fourth section presents the main results, including the central tendency of the average effect size, the heterogeneity across studies, and the mixed effects regression results identifying moderators. The fifth section concludes the findings and limitations of this article and discusses policy implications.

Literature Review

Researchers have long identified clusters' effects on innovation. They propose that clusters may benefit from innovation for several reasons. First, since at least part of the knowledge essential for innovation is elusive and uncodified, knowledge spillovers inside clusters are important for promoting innovation (Jacobs 1970, 1986; M. P. Feldman 1994; Audretsch and Fledman 1996). Second, the deepened specialization inside clusters enables firms to concentrate on limited processes of production, therefore, increases firms' chance of innovation in their specialty (Young 1928; Yang and Ng 1993; Maskell 2001). Third, colocating with rivalries exposes firms to great pressure and motivates them to innovate and maintain competitiveness (Burt 1987; Harrison, Kelley, and Gant 1996; M. E. Porter 1998). Fourth, informal social networks in clusters enable firms to cooperate more intensively and take more risk, which are important for innovation since innovative activities require a large amount of investment and the ability to deal with uncertainty[6] (Gordon and Mccann 2000; Bathelt 2002; Feser and Luger 2003; M. Porter 2003). Fifth, clusters enhance creativity by attracting high-skilled labor and facilitating the communication and collaboration between them (Florida 2006; Florida, Mellander, and Stolarick 2008). Last but not the least, the lowered production costs due to transportation and information costs minimization, shared public intermediate inputs, labor pooling, and so on, enable firms to generate more profits and possibly increase their inputs into the innovative efforts[7] (Marshall 1920; Lichtenberg 1960; Henderson 1986; Von Hippel 1988). All these forces lead to a striking concentration of innovation in the economic landscape (Breschi 1999; Paci and Usai 2000; Wang and Lin 2008).

However, some researchers warn that clusters may also inhibit innovations. First, negative externalities such as congestion and overcompetition are common in clusters (Brezis and Krugman 1993; Baptista 1998). They may lower firms' profits and their inputs into the innovative activities. Second, knowledge spillovers, or by another name "knowledge leakage," may discourage a firm to innovate, since other firms can "free-ride" (Shaver and Flyer 2000; Baten et al. 2004). Third, the rigidity of relationships and repetitive information may lead to the "lock-in" effects, which limit firms' abilities to absorb outside knowledge (Boschma 2005; Moodysson and Jonsson 2007). Because of these forces, although innovation is spatially concentrated, it is not concentrated in a single location. Namely, the dispersing forces are at work (P. Krugman 1998; Beaudry and Breschi 2003).

In addition to the theoretical debate, empirical results are mixed. Many empirical studies detect a positive relationship between clusters and innovation (Aharonson, Baum, and Feldman. 2004; Brenner and Greif 2006; Fornahl, Broekel, and Boschma 2011). Some reveal insignificant relationships (Beugelsdijk and Cornet 2002; Baten et al. 2007; Fitjar and Rodríguez-Pose 2011). Some even find out negative relationships (Acs and Audretsch 1988; Lee 2009). A few recent studies identify mixed results in their own regressions and they suggest some moderators may change the direction and the magnitude of the cluster–innovation relationship (Hamaguchi and Kameyama 2007; Hornych and Schwartz 2009; Fritsch and Slavtchev 2010).

To date, several moderators are identified by individual empirical studies, such as sectors/industries (Shefer and Frenkel 1998; Beaudry 2001; De Beule and Van Beveren 2012), firm size (Acs and Audretsch 1988; Huang, Yu, and Seetoo 2012), firm age (Hamaguchi and Kameyama 2007), the centrality in a network (Bell 2005), whether the clusters are strong in firms' own specialization (Baptista and Swann 1998; Aharonson, Baum, and Feldman 2004), and the magnitude of the specialization/concentration (Hornych and Schwartz 2009; Fritsch and Slavtchev 2010). However, it is hard to generalize beyond individual studies to decide whether these moderators are effective in general. What's more, individual studies usually use data from a single country (even a single region), a single study level (firm, industry, or regional level), and the time frames are limited. Variables such as geographical region, time frame, and study level are hard, if possible, to be identified as moderators in individual studies, despite the fact that their moderating effects may be important.

This article combines the contradicting empirical results in a meaningful way and identifies moderators. By using results from previous empirical studies since the 1980s, this article arrives at a general conclusion based on a super large sample, which includes all the individual samples in the selected studies. Since the sample compasses different countries, industries, centuries, and data levels, moderators undetectable in individual studies can be identified.

Data and Methodology

Data

The empirical studies used in the meta-analysis are collected in three steps: first, a computer search through the first twenty pages of Google Scholar is conducted, based on key word combinations of "cluster" and "innovation," "proximity" and "innovation," and "agglomeration" and "innovation." I browse through the title and abstract and gather the papers appearing to address the cluster–innovation relationship and contain empirical analysis. Since Google Scholar lists literature in an order corresponding to their citations, this computer search covers the most important papers on the topic. I cross-check the results with Web of Science, in which I again search the three groups of key words and sort the results by citation and by relevance. I collect every paper having relevant title and abstract in the first twenty pages. This procedure brings in additional papers missing in Google Scholar. Second, since the above procedure returns mainly published papers (although a few working papers do appear), which may lead to publication bias, I try to include more working papers to mitigate the bias. I search the three combinations of key words in the National Bureau of Economic Research (NBER) working paper and Social Science Research Network (SSRN). NBER working paper contains only working papers and SSRN also contains many, although not restricted to, working papers. For NBER working paper, every paper with the three combinations of key words is collected, since the database is relatively small. For SSRN, again, I sort the search results by citation and by relevance, and collect relevant papers in the first twenty pages. This procedure includes a handful of working papers into the sample. Third, a manual search is carried out. The manual search serves two purposes. First, it includes some newly published papers. Sorting the search results by citations returns more old papers than new papers. To correct that, I manually search the three combinations of key words in Google Scholar and restrict the publication year to be after 2010. I collect relevant papers appear in the first twenty pages of the result. This allows me to include some high-quality and recently published papers that are not yet widely cited. Second, it adjusts for other missing important papers. I browse through the reference lists of collected papers and include relevant references into the sample. This avoids the missing of important papers, because important papers are likely to be cited. Using the above procedure, I collect a total of 263 papers.

However, not all 263 collected papers are used in the meta-analysis. The inclusion criteria are as follows: first, the study needs to be empirical. Theoretical papers are not included in the meta-analysis, though their findings are briefly summarized in the literature review. Second, the empirical study needs to contain regressions or correlation analysis and must have statistical estimation of a coefficient between cluster and innovation. Case studies, papers that simply compare the differences in the means of innovation across in-cluster firms and isolated firms, and papers that separately analyze the determinants of innovation for in-cluster firms and isolated firms[8] are not included. Third, since different studies may use different units in estimation, in order to standardize the estimated coefficients, ideally the studies need to provide descriptive statistics for the means and standard deviations of the dependent and independent variables, or at least enough information for me to recover that information by myself.[9] To increase the sample size, I include studies that do not have sufficient descriptive statistics in the vote-counting part of this article, if they provide enough information to indicate whether the estimated coefficient is significantly different from zero at 5 percent significance level.[10] Without the means and standard deviations, the coefficients cannot be standardized and a comparable effect size cannot be calculated. As a result, these studies are excluded in other parts of the meta-analysis involving effect size. Last, studies that define "cluster" in country level are excluded, because clusters defined in country level are hardly comparable with clusters defined in industry level or regional level. I estimate a mixed effects model including country-level studies and the results show that studies on the country-level report smaller effect size.[11] Using the above procedure, I include a total of seventy papers, 673 regressions, and 1,275 records,[12] in which thirty-two studies are included in the estimation of the average effect size and mixed effects model. Eight working papers are included. Appendix Table A1 lists the sample studies.

Admittedly, many papers addressing the cluster–innovation relationship are excluded under the inclusion criteria. But since this article aims to estimate an average effect size and to analyze which factor influences the estimated effect size, the exclusion of those papers does not affect the result of this article because they do not provide sufficient information on the estimation of an effect size.

Appendix Table A1 shows that the seventy studies are published during 1988 to 2014, mostly on peer-reviewed journals, and have citations varied from 0 to 1,706. Some studies contain only one regression, while some have over forty regressions. The sample size in individual studies varies from less than 50 to as large as 52,920. These studies together with the regressions and records in them constitute a qualified sample for the meta-analysis.

Methodology

There are many reasons for advocating meta-analysis as a rigorous alternative to the traditional narrative review. First, the statistical method has long been acknowledged and widely used in studying relationships between variables. Since individual studies' results (the estimated correlations) and the studies' characteristics (such as time frames, countries, etc.) can also be perceived as potentially correlated variables, there is a compelling reason for the use of the statistical method in analyzing their relationships (Glass 1976; H. M. Cooper and Rosenthal 1980). Second, individual studies suffer more or less from measurement artifacts, limited reliability, restricted research range, small sample size, and low statistical power. Those problems limit the generalization of their results (Borenstein et al. 2011). A combined statistical analysis of the individual studies can overcome many of these limitations and arrive at more general and robust conclusions. Third, when results of individual studies are highly inconsistent, a narrative review usually cannot say anything more than the previous results are mixed. A meta-analysis can draw a general conclusion by estimating the average effect size[13] and testing its significance, despite the heterogeneity across studies. A meta-analysis also explicitly calculates magnitude of the heterogeneity across studies and reveals the effects of the moderators.

This article carries out a meta-analysis to combine the to-date empirical results on cluster–innovation relationships. One difficulty as I mention in the introduction is that the large variations in the "cluster" and "innovation" measurements make the estimation of the average effect size less precise. By estimating the magnitude of heterogeneities across studies, employing the random effects model, and estimating the mixed effects model, this article, taking a similar approach as some other meta-analyses (Damanpour 1991; H. Cooper et al. 2003; Orlitzky, Schmidt, and Rynes 2003), still attempts to arrive at a general conclusion on the relationship between clusters and innovation, no matter how they are defined and measured. It also explores the differences those measurements will make to the estimated effect size. The analysis proceeds as follows. First, it explores the central tendency of the average effect size by vote counting, weighted average, and the fixed effects model. The 95 percent confidence interval of the average effect size is constructed. Second, using Cochrane' Q and I^2 statistics, I test the heterogeneity across studies. The random effects model is applied to reevaluate the average effect size and its 95 percent confidence interval. Third, potential moderators are proposed and tested, using the mixed effects model.

Results

General Conclusions of Clusters' Effects on Innovation

The sampling studies measure clusters and innovation in different ways. Figures 1 and 2 show the various measurements. Because some studies use multiple measurements, the frequencies of measurements are counted in terms of records.[14] The most frequently used measurements of clustering effects, as shown in Figure 1, are distance-related measurement and localization/agglomeration/specialization index. The most frequently used measurements of innovation are the number of innovation/patents per year and a dummy variable indicating whether the firm, industry, or region is innovating. The varied measurements reduce the preciseness of the average effect size estimation, and studies not reporting descriptive statistics cannot generate comparable effect size. To overcome those difficulties, this article first uses a vote-counting method similar to de Groot, Poot, and Smit (2010) based on all sampling records. The vote-counting presents a general picture of the estimated direction of clusters' effects on innovation. Then the average effect size is calculated with subsamples.

The first row of Table 1 shows the vote-counting results of all records. Most records report insignificant effects, and positive effects are reported three times as often as negative effects. The general conclusion therefore appears to be positive.

The results treating every record equally may fail to reveal clusters' overall effects on innovation, because typically a record only represents one characteristic of clusters while clusters can have several characteristics simultaneously affecting innovation. Two additional vote-countings are carried out to

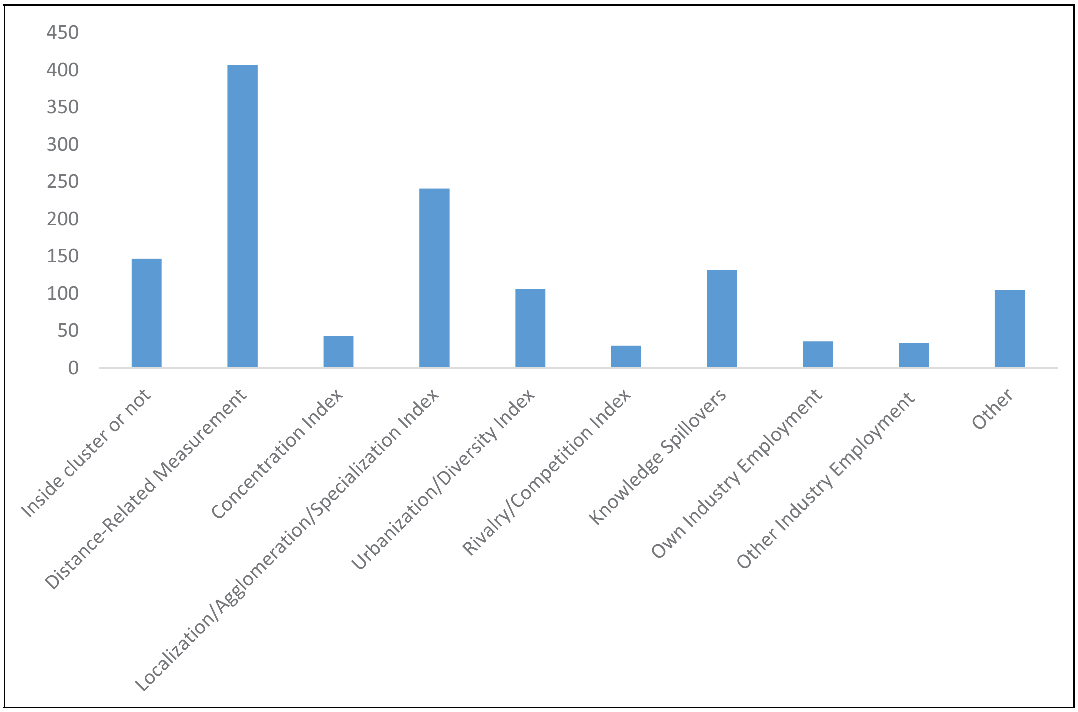

Figure 1. Frequency distribution of cluster measurements in sampling records.

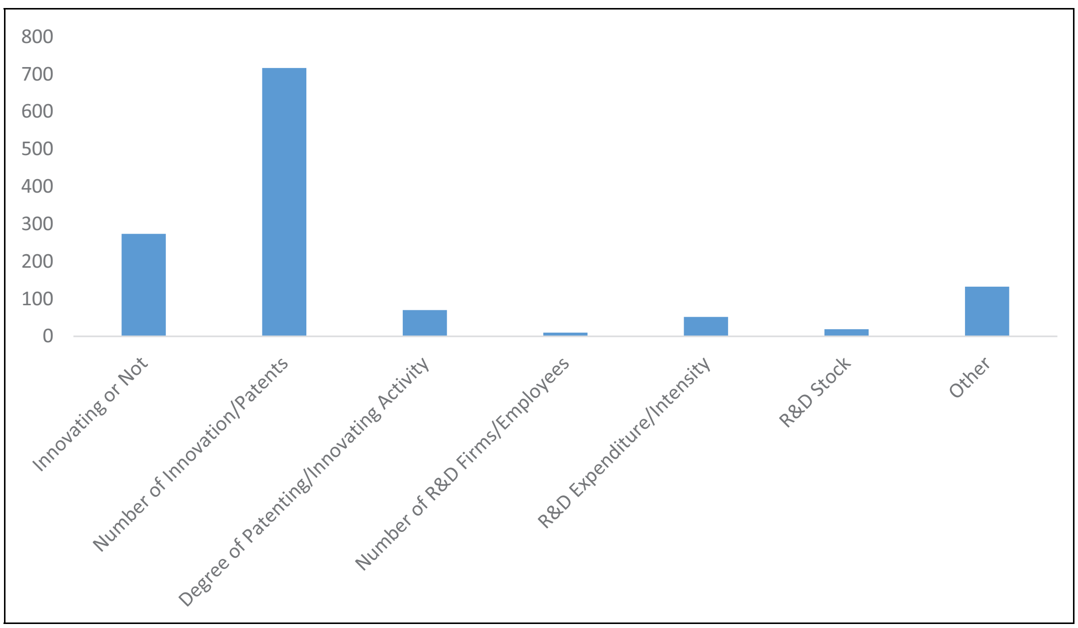

Figure 2. Frequency distribution of innovation measurements in sampling records.

address this problem. The first uses a subsample of records using a dummy variable to measure clustering effects, that is, whether the firm locates in a cluster (if the study is on firm level) or whether the industry or region has a relevant cluster (if the study is on industry or regional level). This dummy variable measures clustering effects in a combined way. The results are shown in the second row of Table 1. A similar pattern is revealed, that many results are insignificant and positive results outnumber negative results. The second counts the estimated direction by regressions instead of records. Since one regression may contain several records (i.e., several characteristics of clusters), the regression-level aggregation of the results can, to some extent, demonstrate clusters' overall effects on innovation. Figure 3 shows most regressions report insignificant effects, and positive effects are reported four times more than negative effects. Some regressions report mixed results, but the

Table 1. The Vote counting of the Estimated Direction of Clusters' Effects on Innovation.

Number of Records	Positive	Negative	Insignificant	Sample Size
Total sample	531	170	574	1,275
Subsample of records measuring cluster with a dummy variable	64	22	61	147

Note: Measuring cluster with a dummy variable means the record uses a dummy variable indicating whether the studied firm locates in a cluster (if the study is on firm level) or whether the studied industry or region has a relevant cluster (if the study is on industry or regional level). Some papers such as Baptista (2000, 2001) measure innovation with time to adopt new technology. The shorter the time, the more innovative the firm is. Therefore, although the signs of coefficients are negative, the effects of clusters on innovation are positive. All the calculations in this article reverse the signs of the relevant coefficients in these papers, to be comparable with other papers.

majority of them are mixed with positive and insignificant effects, which means positive overall effects.[15]

To treat studies equally, a study-level vote counting is done. As different studies contain different number of regressions and records, some studies may be underrepresented in the previous vote countings. The fifth column of Appendix Table A1 shows the study-level vote-counting results. Many studies suggest positive or positive and insignificant effects, and most studies indicate inconclusive results. Only a few find out negative effects.

To summarize, all the vote-counting results show that positive effects are reported more frequently than negative effects. At the same time, most estimated results are insignificant or mixed, indicating there may be moderators shaping the cluster–innovation relationship.

The calculation of the effect size's central tendency is carried out on the subsample in which descriptive statistics of the dependent and independent variables are reported. The effect size is transformed from the original estimated coefficient. It is independent of units and comparable across studies. The effect size reports the magnitude of clusters' effect on encouraging innovation. For economic development practitioners, not only the direction and the significance of the effect are important, the magnitude is also critical. For example, hypothetically, if we find out clusters do have significant positive effects on innovation, but the effect size is only 0.0001, which means one unit standard deviation increase in a certain cluster measurement, innovation increases only by 0.0001 unit standard deviation. This effect is presumably small, no matter what pairs of cluster and innovation measurements are involved. Since initiating a cluster strategy is not costless, economic development practitioners may decide, based on the estimated effect size, that a cluster strategy isn't the way to go in terms of encouraging innovation. On the contrary, if the effect size is 0.1, the cluster strategy becomes more appealing.[16] Generally, an effect size smaller than 0.5 is perceived as a small effect, an effect size between 0.5 and 0.8 is medium, and an effect size above 0.8 is large (Cohen 1988). But clearly, the interpretation of whether the effect size is large enough differs by contexts. Therefore, as to whether estimated effect size in this article makes a cluster strategy worthwhile to pursue, I will leave it open for the practitioners to decide.

The first panel of Table 2 shows the central tendency of the effect size under different weighting methods. The first row shows the unweighting results. The average effect size is 0.045. The median is 0. The peer-review weighted and per year citation[17] weighted average effect size are calculated and presented in the second and third rows, to account for the records' differences in quality. The peer-review weighted results are similar to the unweighted results. When weighted by per year citation,[18] the average effect size increases by 0.6 percent. To treat regressions more equally, the average effect size weighted by regressions is calculated in the fourth row and turns out to be larger (0.059). To treat studies equally, the average effect size weighted by studies is calculated in the fifth row and turns out to be smaller (0.035). Finally, the sixth row uses a sample size weighted method to treat individual sample equally, and the average effect size turns out to be less than half of the results under other weighting schemes.

In order to capture the combined effects of clustering characteristics, I recalculate the average effect size using a subsample in which clusters are measured by a dummy variable. Results are shown in the second panel of Table 2. The average effect size becomes negative (−0.004). The average effect size remains negative under most weighting methods, except for weighted by studies (0.007). This result, combined with the previous results using all samples, indicates that different clustering characteristics have contradicting effects on innovation.

In order to construct the confidence interval for the average effect size, I employ the fixed effects model which assumes different studies report the same effect size and the differences in the actual estimation are caused by random errors. This model reports an average effect size of 0.017, significant at the .001 level with the 95 percent confidence interval (0.016, 0.018).

Heterogeneity across Records and the Random Effects Model

The null hypothesis of homogeneity across records assuming all records report the same effect size is tested against the alternative hypothesis that they are different. The Cochran's Q statistic rejects the null hypothesis at the .001 significance level. In other words, records are heterogeneous in their estimated effect sizes.

However, as some researchers criticize, Cochran's Q has low power when the number of studies is small (Gavaghan, Moore, and McQuay 2000) and too much power when the number of studies is large (Higgins et al. 2003). Therefore, I use the I^2 statistics as a complementary test to ensure the robustness. The I^2 statistic shows 99.268 percent of the variations in the estimated effect size are due to heterogeneity across records.

To account for the heterogeneity, I employ a random effects model which assumes a record-specific effect. The estimated average effect size is 0.045 and is significant at the level of

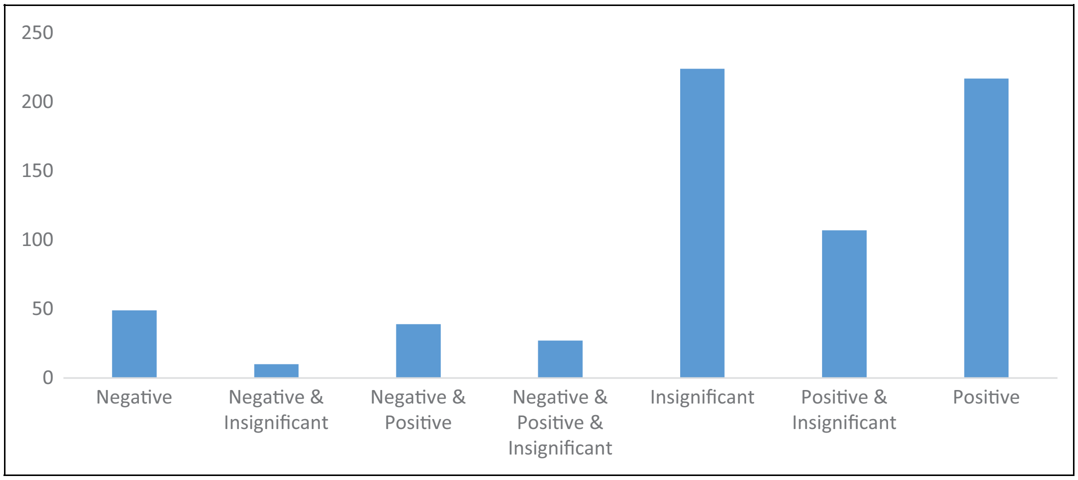

Figure 3. Frequency distribution of the estimated direction in sampling regressions. *Note:* "Positive" means the regression identifies statistically significant positive relationships between some cluster measurements and some innovation measurement. "Negative" and "insignificant" are similarly defined. Since one regression may use several independent variables to measure different clustering characteristics, it can identify positive and negative effects (or other combinations) at the same time. For example, in one regression, localization index shows a negative effect on number of patents per year, while urbanization index shows a positive effect.

Table 2. The Central Tendency of the Effect Size.

Weighting Method	Mean	Median	Standard Deviation	Sample Size (Weighted)
Total sample				
Unweighted	0.045	0	0.183	386
Weighted by peer-review (1.02) and non-peer-review (0.5)	0.046	0	0.183	386.58
Weighted by per year citation	0.051	0	0.331	386
Weighted by regression	0.059	0	0.253	386
Weighted by study	0.035	0	0.155	386
Weighted by sample size	0.017	0	0.353	386
Subsample measuring cluster with a dummy variable				
Unweighted	−0.004	0	0.019	76
Weighted by per year citation	−0.004	0	0.026	76
Weighted by regression	−0.006	0	0.023	76
Weighted by study	0.007	0	0.048	76
Weighted by sample size	−0.002	0	0.036	76

Note: All the weighting methods are standardized so that the total (weighted) sample size keeps the same. For example, in the case of weighting by per year citation, instead of weighting a record with its exact citation, say 25, which would magnify the effect size by twenty-five times, the record is weighted by its exact citation/ average citation. Weighted by regression means every regression is equally weighted as 1.89 (for the total sample), and for the regression having *n* records, every record is weighted 1.89/*n*. Similarly, weighted by study means every study is equally weighted as 14.375 (for the total sample), and for studies having *n* records, every record is weighted 14.375/*n*. For the subsample measuring cluster using a dummy variable, the peer-review weighted effect size is not calculate because all those papers are peer-reviewed.

.001. The 95 percent confidence interval is (0.006, 0.085). The estimated average effect size more than doubles the result from the fixed effects model. The confidence interval is wider, indicating that we are less certain about the average effect size.

Moderating Effects in the Cluster–Innovation Relationship

Moderating effects are explored with the mixed effects model. The mixed effects model uses the estimated effect size from the records as the dependent variable and uses characteristics of the study or of the studied objects as independent variables (Konstantopoulos and Hedges 2004). The coefficients of the independent variables, if significant, indicate the magnitude of the moderating effects. In this article, I first estimate different groups of study characteristics separately and later the joint effect is also estimated. As different groups of study characteristics could be statistically correlated, the joint analysis may yield inefficient estimation. Namely, the coefficients will be less likely to be significant in the joint effect model. Therefore, attention should still be paid to a characteristic if it is insignificant in the joint effect model but significant in the separating effect model.

Tables 3–5 explore the moderating effects of the characteristics of the study itself, including paper quality, model specification, and sample size. Different papers differ in those aspects and that may lead to variations in estimated effect size.

Table 3 explores the moderating effects of paper quality and no effects are found. Model 3-1 uses the mixed effects estimator. Model 3-2 uses the ordinary least squares (OLS) estimator clustered by regressions, so that different records in the same regression are estimated with their correlations taking into consideration. Model 3-3 uses the OLS estimator clustered by studies, so that different records in the same study are estimated with their correlations taking into consideration. In the OLS models, the record-specific random error cannot be estimated,

Table 3. Paper Quality's Moderating Effects.

	Dependent Variable: The Estimated Effect Size					
	Model 3-1: Citation	Model 3-2: Citation	Model 3-3: Citation	Model 3-4: Impact Factor	Model 3-5: Impact Factor	Model 3-6: Impact Factor
	Mixed Effects	OLS Clustered by Regressions	OLS Clustered by Studies	Mixed Effects	OLS Clustered by Regressions	OLS Clustered by Studies
Constant	0.041*** (0.012)	0.042*** (0.011)	0.042 (0.029)	0.040 (0.022)	0.041** (0.015)	0.041 (0.037)
Per-year citation	0.0001 (0.0003)	0.0001 (0.0003)	0.0001 (0.0004)			
Journal impact factor				0.003 (0.006)	0.003 (0.003)	0.003 (0.006)
Adjusted R^2/R^2	−.0002	.0006	.006	−.0002	.0006	.0007
Number of observations	386	386	386	318	318	318

Note: Standard errors/robust standard errors are reported within parentheses. Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
**$p < .01$.
***$p < .005$.

Table 4. Model Specification's Moderating Effects.

	Dependent Variable: The Estimated Effect Size					
	Model 4-1: Mixed Effects		Model 4-2: OLS Clustered by Regressions		Model 4-3: OLS Clustered by Studies	
Constant	0.079***	(0.018)	0.081***	(0.022)	0.081	(0.060)
Negative binomial	−0.065**	(0.024)	−0.067**	(0.024)	−0.067	(0.060)
Logistic	−0.014	(0.032)	−0.022	(0.042)	−0.022	(0.085)
Tobit	−0.036	(0.035)	−0.038	(0.030)	−0.038	(0.061)
OLS	−0.031	(0.030)	−0.032	(0.030)	−0.032	(0.055)
Adjusted R^2/R^2	.0107		.0216		.0216	
Number of observations	386		386		386	

Note: Standard errors/robust standard errors are reported within parentheses.
Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
**$p < .01$.
***$p < .005$.

Table 5. Sample Size's Moderating Effects.

	Dependent Variable: The Estimated Effect Size					
	Model 5-1: Mixed Effects		Model 5-2: OLS Clustered by Regressions		Model 5-3: OLS Clustered by Studies	
Constant	0.053***	(0.011)	0.053***	(0.011)	0.053	(0.026)
Sample size	−1.35e-06	(8.25e-07)	−1.36e-06*	(6.49e-07)	−1.36e-06	(9.70e-07)
Adjusted R^2/R^2	.0041		.0063		.0001	
Number of Observations	386		386		386	

Note: Standard errors/robust standard errors are reported within parentheses.
Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
*$p < .05$.
***$p < .005$.

which may underestimate the heterogeneity across records. Therefore, we primarily trust the results from the mixed effects model and use the other two models to check whether the results are robust or not. Models 3-1 to 3-3 show that when paper quality is proxied by per year citation, it does not affect the effect size. Since the citation of a paper could be affected by its effect size, I use another proxy—journal impact factor—to run the regression (shown in models 3-4 to 3-6), and the results keep the same.

Table 4 explores the model specification's moderating effects and I find studies with negative binomial models estimate a significantly smaller effect size, compared to studies

Table 6. Joint Effects of Study Characteristics.

	Dependent Variable: The Estimated Effect Size					
	Model 6-1: Mixed Effects		Model 6-2: OLS Clustered by Regressions		Model 6-3: OLS Clustered by Studies	
Constant	0.082***	(0.024)	0.085***	(0.030)	0.085	(0.089)
Per year citation	−0.00004	(0.0003)	−0.0006	(0.003)	−0.0006	(0.0007)
Negative binomial	−0.061*	(0.026)	−0.064*	(0.028)	−0.064	(0.071)
Logistic	−0.017	(0.034)	−0.025	(0.045)	−0.025	(0.102)
Tobit	−0.038	(0.037)	−0.041	(0.034)	−0.041	(0.084)
OLS	−0.030	(0.031)	−0.032	(0.033)	−0.032	(0.066)
Sample size	−6.22e-07	(9.23e-07)	−6.28e-07	(5.79e-07)	−6.28e-07	(5.79e-07)
Adjusted R^2/R^2	.0064		.0228		.0228	
Number of observations	386		386		386	

Note: Standard errors/robust standard errors are reported within parentheses. Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
*$p < .05$.
***$p < .005$.

with other models. Model 4-1 shows that when the negative binomial model is used, the estimated effect size shrinks by 80 percent, compared with when other models are used. This result keeps robust in model 4-2, but turns insignificant in model 4-3. R^2 indicates the model specification explains 2 percent of the variations in the effect size. This moderating effect can be caused by two reasons. First, since the negative binomial model is a counting model, it is possible that whenever innovation is measured by the counting variable, such as number of patents/innovation/research and development (R&D) firms/R&D employees, the effect size is smaller no matter what model is used. Second, it is also possible that even within the subgroup of studies measuring innovation with the counting variable, when different models are employed, the effect size varies. To differentiate between the two potential explanations, I run the regression with the subgroup of studies using counting variable in Appendix Table A2. The results show that the moderating effect of negative binomial model still exists within the subgroup. Moreover, the logistic model also has a negative moderating effect in model A2-1 and A2-2. The Tobit model shows a negative moderating effect in model A2-2. Those results indicate the model specification does affect the effect size: the OLS model reports the largest positive effect size, the negative binomial model reports an average effect size only 10 percent as large, the logit model reports a negative effect size, and for the Tobit model the result is inconclusive. OLS estimator, generally speaking, is not appropriate to be used on counting data[19]; therefore, the abovementioned results suggest the effect size is considerably smaller when we specify the model suitably.

Table 5 estimates sample size's moderating effect. A negative moderating effect is found in model 5-2 while the other two models report insignificant effects.

Table 6 presents the joint effect results. Only the negative binomial model shows a significant negative moderating effect in models 6-1 and 6-2, and as expected, the significance level drops. The study characteristics jointly account for 2 percent of variations in the effect size. An implication for future study on the cluster–innovation relationship is model specification matters and researchers should put more efforts into correctly specifying their models.

Tables 7–13 explore the moderating effects of the studied objects' characteristics, such as measurements of clusters and innovation, industries, and study level. The differences in those characteristics can be interpreted as the differences in the actual concerned relationships. For example, studies measuring innovation by a dummy indicating whether the agent is innovating or not can be interpreted as caring about only the differences in non-innovating agents and agents that innovate at least something, while studies measuring innovation by the number of patents per year can be interpreted as caring also about the differences across innovating agents. Exploring the potential moderating effects of those characteristics can provide some guidance for economic development practitioners in their evaluation of whether a cluster strategy can encourage innovation in the local jurisdiction and by how much.

Table 7 explores the moderating effects of cluster measurements, and several measurements are found to have significant effects. R^2 indicates over 18 percent of the variations in the effect size are explained by cluster measurements. The inside cluster or not dummy shows a significant negative moderating effect in models 7-1 and 7-2. A study measuring clusters with this variable on average reports an effect size of −0.004, which indicates that different characteristics of clusters may have contradicting effects on innovation, causing the overall effect to be small and negative.

The concentration index shows a significant negative effect in all three models, and the magnitude is larger than all other measurements' effects. A study measuring clusters with the concentration index on average reports an effect size of −0.117. Several mechanisms can explain such an effect. First, the absence of competition under high concentration cuts firms' motivation to innovate (M. E. Porter 1990). Second, more small firms searching for innovation naturally yield a higher chance of success (Geroski 1990). Third, firms with monopoly power gets lower net return from new innovation

Table 7. Cluster Measurement's Moderating Effects.

	Dependent Variable: The Estimated Effect Size		
	Model 7-1: Mixed Effects	Model 7-2: OLS Clustered by Regressions	Model 7-3: OLS Clustered by Studies
Constant	0.065*** (0.019)	0.064*** (0.018)	0.064 (0.047)
Inside cluster or not	−0.069* (0.028)	−0.068*** (0.018)	−0.068 (0.047)
Distance-related measurement	−0.043 (0.041)	−0.044 (0.023)	−0.044 (0.046)
Concentration index	−0.182*** (0.038)	−0.181*** (0.041)	−0.181** (0.063)
Localization/agglomeration/specialization index	0.139*** (0.031)	0.142** (0.054)	−0.142 (0.121)
Urbanization/diversity index	−0.043 (0.052)	−0.029 (0.050)	−0.029 (0.084)
Rivalry/competition index	−0.039 (0.046)	−0.039 (0.025)	−0.039 (0.047)
Knowledge spillovers	−0.003 (0.027)	−0.003 (0.026)	−0.003 (0.053)
Own industry employment	−0.081 (0.041)	−0.079* (0.038)	−0.079 (0.051)
Other industry employment	−0.062 (0.043)	−0.061*** (0.022)	−0.061 (0.049)
Adjusted R^2/R^2	.1674	.1803	.1803
Number of observations	386	386	386

Note: Standard errors/robust standard errors are reported within parentheses. Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
*p < .05.
**p < .01.
***p < .005.

Table 8. Innovation Measurement's Moderating Effects.

	Dependent Variable: The Estimated Effect Size					
	Model 8-1: Mixed Effects		Model 8-2: OLS Clustered by Regressions		Model 8-3: OLS Clustered by Studies	
Constant	0.064**	(0.024)	0.063**	(0.024)	0.063	(0.040)
Innovation or not	−0.039	(0.034)	−0.039	(0.029)	−0.039	(0.044)
Number of innovation/patents per year	−0.009	(0.027)	−0.006	(0.027)	−0.006	(0.051)
Degree of patenting/innovating activity	−0.040	(0.142)	−0.043	(0.028)	−0.043	(0.042)
R&D expenditure/ intensity	−0.084	(0.044)	−0.082***	(0.024)	−0.082**	(0.040)
R&D stock	−0.049	(0.048)	−0.046	(0.068)	−0.046	(0.110)
Adjusted R^2/R^2	.0015		.0152		.0152	
Number of observations	386		386		386	

Note: Standard errors/robust standard errors are reported within parentheses.
Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model. R&D = research and development.
**p < .01.
***p < .005.

than new entrants because the new innovation replaces the old one they are currently using (Fellner 1951; Arrow 1962).

The localization/agglomeration/specialization index shows a significant positive effect in models 7-1 and 7-2. A study measuring clusters with those indexes on average reports an effect size of 0.204. Localization/agglomeration/specialization facilitates imitation and information exchange, which are beneficial for innovation (Knoben 2009; Marrocu, Paci, and Usai 2013), and such positive effects outweigh negative effects such as congestion.

But congestion still exists, as in model 7-2, own industry employment and other industry employment exhibit significant negative moderating effects. Several studies suggest that clusters strong in specialization other than the firm's own industry have insignificant or even negative effects due to congestion (Baptista and Swann 1998; Aharonson, Baum, and Feldman 2004).

Table 8 explores innovation measurements' moderating effects and only one measurement—R&D expenditure/intensity—shows a significant negative effect in models 8-2 and 8-3. A study using R&D expenditure/intensity to measure innovation on average reports an effect size of −0.019. It makes sense because R&D expenditure/intensity is a measurement focusing more on innovation input than innovation output. Clusters may have limited, zero, or even negative effects on innovation input, while still have notable positive effects on innovation output.

Table 9 explores different industries' moderating effects, and several industries turn out to have significant effects. R^2

Table 9. Industry's Moderating Effects.

	Dependent Variable: The Estimated Effect Size					
	Model 9-1: Mixed Effects		Model 9-2: OLS Clustered by Regressions		Model 9-3: OLS Clustered by Studies	
Constant	0.180*	(0.081)	0.176	(0.133)	0.176	
All	−0.160	(0.082)	−0.156	(0.133)	−0.156***	(0.013)
Manufacturing	−0.034	(0.083)	−0.030	(0.137)	−0.030	(0.083)
Service	−0.201*	(0.089)	−0.197	(0.134)	−0.197	
Innovation/High-tech	−0.174*	(0.088)	−0.169	(0.134)	−0.169***	(0.013)
Biotechnology	−0.142	(0.086)	−0.135	(0.133)	−0.135***	(0.014)
Chemistry	−0.180	(0.118)	−0.176	(0.133)	−0.176	
Adjusted R^2/R^2	.0742		.0900		.0900	
Number of observations	386		386		386	

Note: Standard errors/robust standard errors are reported within parentheses.
Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
*$p < .05$.
***$p < .005$.

Table 10. Study Level's Moderating Effects.

	Dependent Variable: The Estimated Effect Size					
	Model 10-1: Mixed Effects		Model 10-2: OLS Clustered by Regressions		Model 10-3: OLS Clustered by Studies	
Constant	2.26e-15	(0.818)	1.09e-15		1.09e-15	(8.60e-09)
Firm/establishment	0.027	(0.082)	0.027***	(0.007)	0.027*	(0.012)
Region	0.338***	(0.089)	0.339***	(0.080)	0.339*	(0.151)
Adjusted R^2/R^2	.1484		.1633		.1633	
Number of observations	386		386		386	

Note: Standard errors/robust standard errors are reported within parentheses.
Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
*$p < .05$.
***$p < .005$.

indicates that industries explain 9 percent of the variations in the effect size. This result supports the argument made in previous studies that sectors and industries have moderating effects on the cluster–innovation relationship (Shefer and Frenkel 1998; Beaudry 2001; De Beule and Van Beveren 2012). When data from various industries are used in a study, a negative moderating effect appears in model 9-3, which indicates clusters do not equally encourage innovation in all industries. The service industry shows a negative moderating effect by a magnitude of 0.2 in model 9-1, suggesting in service industry, clustering hinders innovation. Surprisingly, the innovation/high-technology industry also shows a negative moderating effect in model 9-1 and 9-3, and the biotechnology industry shows a negative moderating effect in model 9-3. Model 9-3 indicates that in the innovation/high-technology industry, clusters on average have an effect size of 0.007 on innovation, and in the biotechnology industry, the average effect size is 0.04. Intuitively, one would suspect that cluster should strongly encourage innovation in these industries, but the evidence suggests the opposite. One possible explanation is that those industries are innovative anywhere, therefore locating in clusters, although do add an extra positive effect on innovation, the effect size is relatively small. Huang, Yu, and Seetoo (2012) suggests while locating in science parks in general helps innovation, firms with inferior R&D capabilities benefit more. Because firms in the innovation, high-technology, and biotechnology industries in general have higher R&D capabilities, they benefit less by locating in clusters. Appendix Table A3 presents a preliminary evidence supporting this explanation. In both industries, positive effect size outnumbers negative effect size, and the average is smaller than the average effect size in the whole sample (0.045). The maximum and minimum are all reasonable. Therefore, the only explanation is most positive effect sizes are small in magnitude.

Table 10 explores the study level's moderating effects, and studies on different level are found to report different effect sizes. Studies on firm/establishment level show a positive effect in models 10-2 and 10-3, while regional-level studies show a positive effect in all three models. The differences in study levels explain over 16 percent of the variations in the effect size. Since most individual studies study only one level, limited attention to date has been devoted to this moderating effect. This effect demonstrates that although individual firms/establishments do benefit from clusters, the positive effect of clusters largely exists external to them. Ninety-two percent of

Table 11. Firm Size's Moderating Effects.

	Dependent Variable: The Estimated Effect Size					
	Model 11-1: Mixed Effects		Model 11-2: OLS Clustered by Regressions		Model 11-3: OLS Clustered by Studies	
Constant	0.045***	(0.009)	0.045***	(0.009)	0.045*	(0.022)
Large	−0.045	(0.081)	−0.045***	(0.009)	−0.045*	(0.022)
Small	0.046	(0.070)	0.043	(0.032)	0.043	(0.043)
Adjusted R^2/R^2	−.0033		.0018		.0018	
Number of observations	386		386		386	

Note: Standard errors/robust standard errors are reported within parentheses.
Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
*p < .05.
***p < .005.

Table 12. Geographical Region's Moderating Effects.

	Dependent Variable: The Estimated Effect Size					
	Model 12-1: Mixed Effects		Model 12-2: OLS Clustered by Regressions		Model 12-3: OLS Clustered by Studies	
Constant	0.029	(0.021)	0.028	(0.019)	0.028	(0.023)
America	0.053	(0.029)	0.052*	(0.027)	0.052*	(0.032)
Europe	0.014	(0.025)	0.017	(0.023)	0.017	(0.040)
Asia	−0.026	(0.037)	−0.025	(0.019)	−0.025	(0.023)
Adjusted R^2/R^2	.0083		.0147		.0147	
Number of observations	386		386		386	

Note: Standard errors/robust standard errors are reported within parentheses.
Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
*p < .05.

the positive effect is exhibited on the regional level, which can only be absorbed through within-cluster cooperation.

Table 11 explores firm size's moderating effects, and large firms are found to have negative moderating effects. Models 11-2 and 11-3 suggest large firms do not benefit in terms of innovation, which is in line with previous studies (Huang, Yu, and Seetoo 2012). The positive effect is absorbed by small- and medium-sized firms. R^2 shows firm size explains 2 percent of the variations in the effect size.

Table 12 explores the geographical regions' moderating effects, and America turns out to have a significant positive moderating effect in model 12-2. Studies on America report an average effect size of 0.052, while studies on other continents do not report a significant positive effect size. Asia even has a negative moderating effect, although insignificant. Since most of the individual studies are based on only one continent, this moderating effect is seldom noticed in previous studies. Compared with clusters in America, clusters in Europe suffer from imperfect market integration and institutional and cultural barriers (Crescenzi, Rodríguez-Pose, and Storper 2007). In Asia, clusters are usually created by governments, and when market forces are insufficient to support the emergence of a cluster, the cluster's effect on innovation becomes limited.

Table 13 explores the time frame's moderating effects. The year 1970 and before shows a significant negative effect in all three models and clusters during that time hinders innovation with the average effect size −0.022. But after 1970s, clusters promote innovation. This may be because clusters before 1970 are underdeveloped and immature. The time frame explains 4 percent of the variations in the effect size.

Table 14 presents the joint effects of the studied objects' characteristics. Cluster measurements still show the same moderating effects as in Table 7, while innovation measurements now exhibit positive moderating effects in model 14-2. But this does not contradict the results of Table 8. Almost all innovation measurements showing positive moderating effects except R&D expenditure/intensity are equivalent to the results in Table 8 where only R&D expenditure/intensity shows a negative moderating effect. The service industry shows a negative moderating effect in all three models, consistent with Table 9. Every industry shows a negative moderating effect in model 14-3, including the manufacturing and the chemical industries that are insignificant in Table 9. Since the manufacturing industry shows the smallest negative moderating effect among all industries, this result is still consistent with Table 9. Both results (Table 9 and 14) indicate the manufacturing industry benefits the most from locating in clusters. Same with Table 10, the regional-level study has a positive moderating effect. Small firm has a significant positive moderating effect, equivalent to the results of Table 11 where large firm has a significant negative effect. Geographical regions and time frame are no longer significant in the joint model. Those characteristics

Table 13. Time Frame's Moderating Effects.

	Dependent Variable: The Estimated Effect Size					
	Model 13-1: Mixed Effects		Model 13-2: OLS Clustered by Regressions		Model 13-3: OLS Clustered by Studies	
Constant	0.060*	(0.025)	0.060*	(0.026)	0.060***	(0.012)
1970 and before	−0.088*	(0.038)	−0.088***	(0.031)	−0.088**	(0.031)
1980–1990	0.058	(0.041)	0.058	(0.050)	0.058	(0.043)
1990–2000	−0.034	(0.027)	−0.034	(0.026)	−0.034	(0.017)
2000 and after	0.021	(0.030)	0.021	(0.034)	0.021	(0.067)
Adjusted R^2/R^2	.0341		.0415		.0415	
Number of observations	386		386		386	

Note: Standard errors/robust standard errors are reported within parentheses.
Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
*$p < .05$.
**$p < .01$.
***$p < .005$.

Table 14. Joint Effects of Object Characteristics.

	Dependent Variable: The Estimated Effect Size		
	Model 14-1: Mixed Effects	Model 14-2: OLS Clustered by Regressions	Model 14-3: OLS Clustered by Studies
Constant	0.178 (0.127)	0.177 (0.153)	0.177*** (0.055)
Inside cluster or not	−0.083 (0.063)	−0.073* (0.036)	−0.073 (0.049)
Distance-related measurement	−0.029 (0.040)	−0.034 (0.022)	−0.034 (0.025)
Concentration index	−0.256*** (0.042)	−0.255*** (0.052)	−0.255** (0.093)
Localization/agglomeration/specialization index	0.114* (0.055)	0.118* (0.058)	0.118 (0.095)
Urbanization/diversity index	0.011 (0.066)	0.014 (0.067)	0.014 (0.094)
Rivalry/competition index	−0.078 (0.053)	−0.079 (0.059)	−0.079 (0.043)
Knowledge spillovers	0.033 (0.029)	0.037 (0.024)	0.037 (0.037)
Own industry employment	−0.147*** (0.040)	−0.144** (0.055)	−0.144 (0.071)
Other industry employment	−0.131*** (0.041)	−0.129*** (0.038)	−0.129 (0.076)
Innovation or not	0.076 (0.048)	0.071* (0.035)	0.071 (0.041)
Number of innovation/patents per year	0.074 (0.042)	0.069* (0.032)	0.069 (0.055)
Degree of patenting/innovating activity	0.121 (0.139)	0.102* (0.046)	0.102 (0.059)
R&D expenditure/intensity	0.129 (0.139)	0.112 (0.063)	0.112 (0.083)
R&D stock	0.088 (0.054)	0.088 (0.060)	0.078 (0.073)
All	−0.137 (0.077)	−0.135 (0.144)	−0.135*** (0.024)
Manufacturing	−0.103 (0.081)	−0.097 (0.139)	−0.097*** (0.029)
Service	−0.384*** (0.095)	−0.381*** (0.145)	−0.381*** (0.043)
Innovation/High-tech	−0.153 (0.081)	−0.149 (0.139)	−0.149*** (0.026)
Biotechnology	−0.144 (0.081)	−0.141 (0.145)	−0.141*** (0.035)
Chemistry	−0.197 (0.122)	−0.187 (0.145)	−0.187*** (0.059)
Firm/establishment	0.067 (0.096)	0.069 (0.044)	0.069 (0.059)
Region	0.220* (0.102)	0.220*** (0.067)	0.220* (0.093)
Large	−0.029 (0.074)	−0.025 (0.029)	−0.025 (0.020)
Small	0.083 (0.064)	0.085*** (0.027)	0.085*** (0.018)
America	0.069 (0.064)	0.062 (0.034)	0.062 (0.037)
Europe	0.018 (0.055)	0.011 (0.038)	0.011 (0.031)
Asia	−0.069 (0.088)	−0.086 (0.060)	−0.086 (0.076)
1970 and before	−0.087 (0.069)	−0.081 (0.064)	−0.081 (0.053)
1980–1990	−0.172 (0.105)	−0.175 (0.115)	−0.175 (0.133)
1990–2000	−0.180 (0.094)	−0.176 (0.101)	−0.176 (0.131)
2000 and after	−0.043 (0.059)	−0.039 (0.071)	−0.039 (0.054)
Adjusted R^2/R^2	.3245	.3842	.3842
Number of observations	386	386	386

Note: Standard errors/robust standard errors are reported within parentheses. Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model. R&D = research and development.
*$p < .05$.
**$p < .01$.
***$p < .005$.

Table 15. Summary of Moderating Effects.

Moderators	Direction of Effects	Number of Models Finding the Effect	Relationship with Previous Studies
Negative binomial	−	4	New
Sample size	−	1	New
Inside cluster or not	−	3	New
Concentration index	−	6	New
Localization/ agglomeration/ specialization index	+	4	New
Own industry employment	−	3	Different
Other industry employment	−	3	Same
Innovation or not	+	1	New
Number of innovation/patents per year	+	1	New
Degree of patenting/ innovating activity	+	1	New
R&D expenditure/ intensity	−	2	New
All industry	−	2	New
Manufacturing	−	1	New
Service	−	4	New
Innovation/high-tech	−	3	New
Biotechnology	−	2	New
Chemistry	−	1	New
Firm/establishment	+	2	New
Region	+	6	New
Large	−	2	Same
Small	+	2	Same
America	+	2	New
1970 and before	−	3	New

Note: Relationship with previous studies means whether this results is in line with previous studies (denoted by "Same"), contrary to previous studies (denoted by "Different") or not mentioned in previous studies (denoted by "New"). R&D = research and development.

of the studied objects jointly account for 38 percent of the variations in the effect size. Generally speaking, the results of the joint effect model are consistent with the separating effects, but because of the potential correlations between factors, the estimation is less efficient, meaning that the coefficients are more likely to be insignificant. Therefore, factors insignificant in the joint effect model but significant in the separating effect model should still be taken into consideration when thinking of initiating a cluster strategy to promote innovation.

Table 15 summarizes the moderators identified in this article. Most moderators exhibit negative moderating effects, while some have positive effects. Most results are new additions to our current understanding of the cluster–innovation relationship, for example, the moderating effects of cluster measurements, innovation measurements, the study level, the geographical regions, time frames, and so on. Many other results are in line with previous studies. In sum, these moderators jointly account for 38 percent of the variations in the effect size, in which cluster measurements account for the largest share, followed by the study level and the industry. The separating effect models and the joint effect model can be used to analyze the direction of a specific cluster's effect on innovation, and the joint effect model can be used to predict the magnitude of the effect size.

Conclusion

By conducting a meta-analysis on available empirical studies since the 1980s addressing the cluster–innovation relationship, this article yields the following results. (1) Clusters on average have positive effects on innovation. (2) Heterogeneity across studies is large. (3) Several variables serve as moderators in clusters' effects on innovation, such as measurements of clusters, industry, firm size, and so on. Many of the moderators haven't been uncovered by previous studies. (4) Some variations in clusters' effect on innovation remain unexplained.

This article has four major limitations. First, like all meta-analysis and all literature reviews, this article cannot avoid publication bias, meaning papers with significant results are more likely to be published and therefore included in this research. The fact that I try to include many working papers into the sample may to some extent mitigate this bias. Second, because of heterogeneity across studies, the average effect size estimated in this article provides limited information on the magnitude of the cluster–innovation relationship. Since many studies do not report descriptive statistics, they have to be excluded in the statistical calculation of this article (but included in the vote-counting part), which again limits the information that can be used. Third, some of the moderators identified in previous studies cannot be tested in this article. For example, Bell (2005) suggests that the centrality in a network could be a moderator. However, since few studies measure the firm's centrality in networks, this argument is not tested in this article. Fourth, as the meta-analysis is limited to the data we have in previous studies, some moderating effects found out in this article are not well explained and the mechanisms behind them remain uncovered. For example, why clusters cannot bring innovation before 1970? Instead of fully answering the questions, this article simply identifies these effects and calls for future research.

This article provides useful guidance for economic development practitioners and local authorities. It shows that an average cluster does have a positive effect on innovation. But no certain conclusion can be said to a specific cluster without taking moderators into consideration. Some of the factors are what characteristics the cluster has (Does it have more concentration? Or does it have more localization effect?), the size of the firms inside the cluster, the industry that the cluster is specialized in, and so on. Without taking these specific conditions into consideration, local authorities' enthusiasm in supporting clusters may turn out to have no effect, or even negative effect on innovation against their good intention. Therefore, this article suggests local economic development strategies should be state-contingent. This article provides at least preliminary guidance on how to evaluate the direction and magnitude of a specific cluster's effect on innovation. For example, suppose a US local government is considering to take a cluster strategy to increase the number of patents in the region and the local industries are mostly manufacturing. Ignoring other factors for simplicity,[20] a cluster measured in a combined way exhibits an effect size of −0.004 (Table 7); when number of patent is concerned, the effect size is 0.055 (Table 8); when regional-level success is concerned, the effect size is 0.338 (Table 10); a US cluster exerts an effect size of 0.082 and a cluster after 2000 exerts an effect size of 0.081 (Tables 12 and 13); and the manufacturing industry has an effect size of 0.146 (Table 9). After combining the above factors, we can conclude such a cluster on average is expected to encourage innovation, because the positive effects outweigh the negative effects. To more precisely estimate the overall effect size, we can use the results from Table 14. The expected effect size is 0.312, and it is significantly different from zero at the .01 level. The expected effect size indicates, if the probability of a cluster being formed in the region increases by one unit of standard deviation, the number of patents per year would approximately increase by 0.312 unit of standard deviation. The weighted sample average deviation of the probability of clustering is 0.396, and the weighted sample average deviation of patent counts is 19.790. If we estimate the population standard deviations by the sample deviations, the above result can be further interpreted as once a cluster is formed in the region, compared with no presence of a cluster, approximately fifteen more patents per year would be produced. If collecting all relevant data is costly, this article identifies some important moderators that should be given prior considerations: whether the local industries have high-concentration, high-localization effect, strong in one industry or in several industries, whether the local governments try to improve firm-level innovation performance or regional-level innovation performance, and what is the major or concerned industry. Finally, it's worth mentioning that this article only focuses on innovation, while local authorities may decide to pursue a cluster strategy for other considerations. Therefore, this article itself does not provide a full guidance regarding the suitability of a cluster strategy for a certain local jurisdiction. But it provides some useful implications, and together with studies focusing on other outcomes of clusters, such as employment growth and productivity, this article can narrow down local authorizers' considerations to a few important factors when deciding the initiation of a cluster strategy.

Appendix

Table A1. The Sampling Studies and Their Estimation of the Cluster–Innovation Relationship.

Studies	Total Citation	Number of Regressions	Number of Records	Estimation Results	Sample Size
Acs and Audretsch (1988)	1,706	6	11	−	247
Baptista and Swann (1998)	1,099	10	47	o	1,984
Shefer and Frenkel (1998)	144	4	4	o	122
Blundell, Griffith, and Van Reenen (1999)	997	12	12	o	3,511
Brouwer, Budil-Nadvornikova, and Kleinknecht (1999)	96	2	2	++	4,296
Feldman and Audretsch (1999)	1,479	13	28	o	5,946
Love and Roper (1999)	211	1	1	++	725
Paci and Usai (2000b)	82	10	53	o	9,265
Baptista (2000)	396	3	6	+o	1,035
Broberg (2001)	0	6	14	+o	1,588
Roper et al. (2000)	38	2	2	o	1,239
Baptista (2001)	119	6	12	+o	1,035
Beaudry (2001)	69	21	62	o	538
Sternberg and Arndt (2001)	198	3	3	+o	1,774
Wallsten (2001)	152	93	106	o	49,589
Beugelsdijk and Cornet (2002)	41	6	18	+o	1,510
Maurseth and Verspagen (2002)	340	3	3	++	12,432
Smith, Broberg, and Overgaard (2002)	24	4	8	o	1,285
Beaudry and Breschi (2003)	227	12	40	o	37,724
Bottazzi and Peri (2003)	595	44	142	+o	86
Van Der Panne and Dolfsma (2003)	21	4	4	o	43
Aharonson, Baum, and Feldman (2004)	0	3	6	+o	2,121
Baten et al. (2004)	3	5	25	o	37,724
Bönte (2004)	27	1	1	−	178
Mariani (2004)	29	4	8	+o	3,518
Bell (2005)	404	1	1	o	64
Brenner and Greif (2006)	55	28	28	+o	97

(continued)

Table A1. (continued)

Studies	Total Citation	Number of Regressions	Number of Records	Estimation Results	Sample Size
Folta, Cooper, and Baik (2006)	158	4	8	o	2,346
Gilbert and Kusar (2006)	2	6	8	+o	128
Baten et al. (2007)	17	2	4	o	43
Beugelsdijk (2007)	65	7	35	o	1,466
Boufaden, Boufaden, and Plunket (2007)	13	2	2	++	240
Van Geenhuizen and Reyes-Gonzalez (2007)	37	2	2	+o	85
Johansson and Lööf (2008)	49	2	2	+o	2,094
Czarnitzki and Hottenrott (2009)	34	4	4	o	1,265
Hornych and Schwartz (2009)	24	1	1	++	377
Knoben (2009)	33	3	24	o	203
Lee (2009)	31	22	22	−o	1,458
Fritsch and Slavtchev (2010)	36	2	3	o	93
Fitjar and Rodríguez-Pose (2011)	24	4	4	+o	1,602
Fornahl, Broekel, and Boschma (2011)	33	10	10	+o	642
Presutti, Boari, and Majocchi (2011)	8	2	2	o	210
De Beule and Van Beveren (2012)	5	14	28	+o	3,205
Huang, Yu, and Seetoo (2012)	6	3	9	o	864
Lecocq et al. (2012)	5	3	4	o	422
Bloom, Schankerman, and Van Reenen (2013)	227	16	32	+o	9,122
Chyi and Liao (2010)	0	2	2	o	548
Antonietti and Cainelli (2011)	39	5	20	o	715
Baptista (2001)	134	6	6	+o	11,671
Boufaden and Plunket (2005)	10	2	6	+o	75
Crescenzi, Rodríguez-Pose, and Storper (2007)	217	41	46	o	145
De Beule and Van Beveren (2008)	0	8	8	+o	3,303
Delgado, Porter, and Stern (2012)	83	2	6	o	40,266
D'Este, Guy, and Iammarino (2013)	51	5	7	+o	52,920
Johansson and Lööf (2008)	54	5	5	o	2,094
Khan (2014)	0	19	36	−o	25,505
De Dominicis, Florax, and De Groot (2013)	10	4	4	++	146
Marrocu, Pasi, and Usai (2013)	14	14	24	o	276
Molina-Morales, García-Villaverde, and Parra-Requena (2011)	7	6	18	+o	415
Moreno, Paci, and Usai (2005)	109	18	54	+o	1,225
Mukim (2012)	0	20	48	+o	3,557
Nishimura and Okamuro (2011)	34	9	9	o	197
Shearmur (2011)	50	10	22	+o	3,161
Van Oort (2002)	57	9	27	o	580
Vásquez-Urriago et al. (2011)	6	32	32	+o	39,722
Weterings and Boschma (2009)	72	4	6	+o	194
Žižka and Rydvalová (2014)	0	6	6	o	79
Harrison, Kelley, and Gant (1996)	352	21	21	+o	962
Link and Scott (2003)	162	6	6	+o	29
Chen (2011)	1	2	2	++	108

Note: See note 12 for the definition of records. The sample size reported here is defined as the largest sample size in a study, since regressions in the same paper may have different sample sizes. ++ = positive in all cases; +o = positive in some cases and insignificant in others; o = inconclusive, which means insignificant in all cases, positive in some cases and negative in others, or positive in some cases, negative in some cases and insignificant in others; −o = negative in some cases and insignificant in others; − = negative in all cases.

Table A2. Model Specification's Moderating Effects.

	Dependent Variable: The Estimated Effect Size					
	Model A2-1: Mixed Effects		Model A2-2: OLS Clustered by Regressions		Model A2-3: OLS Clustered by Studies	
Constant	0.163***	(0.027)	0.167***	(0.040)	0.167	(0.113)
Negative binomial	−0.149***	(0.021)	−0.153***	(0.041)	−0.153	(0.113)
Logistic	−0.202**	(0.073)	−0.205***	(0.040)	−0.205	(0.113)
Tobit	−0.163	(0.138)	−0.167***	(0.040)	−0.167	(0.113)
OLS	−0.042	(0.044)	−0.046	(0.050)	−0.046	(0.088)
Adjusted R^2/R^2	.0119		.1201		.1201	
Number of observations	225		225		225	

Note: Standard errors/robust standard errors are reported within parentheses.
Adjusted R^2 is reported for the mixed effects model and R^2 is reported for the clustered ordinary least squares (OLS) model.
**$p < .01$.
***$p < .005$.

Table A3. The Estimated Effect Size in the Innovation/High-tech and Biotechnology Industries.

Number of Negative Effect Size	Number of Positive Effect Size	Number of Insignificant Effect Size	Average Effect Size	Minimum Effect Size	Maximum Effect Size	Sample Size
Innovation/High-tech						
4	11	12	0.013	−0.026	0.199	27
Biotechnology						
1	11	25	0.040	−0.004	0.393	37

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Notes

1. Such as Boufaden, Boufaden, et al. (2007) uses a spatial matrix of seven neighboring regions, which certainly overlooks other regions in proximity (e.g., near but not contingent).
2. Therefore, they do not even calculate an average effect size.
3. The results of de Groot, Poot, and Smit (2010) are relatively hard to interpret, since they use studies with very different dependent variables (such as employment growth, productivity growth, and innovation), unless they impose the strong assumptions that all these dependent variables lead to regional economic growth, which is clearly not always true (Eriksson 1997). Therefore, if we obtain a significant positive average effect size in such an analysis, we can only interpret that as clusters in general are helping the local economies in some ways. More explicit and clear interpretation is not applicable. Since this article restricts the dependent variable to be innovation-related variables, if we obtain a significant positive average effect size, we can interpret it more explicitly as clusters in general benefit innovation.
4. By saying smaller sample size, I am comparing the sample size in this article with the counterfactual situation of the sample size that I would have if I define the concerned dependent variables as broad as de Groot, Poot, and Smit (2010), rather than directly comparing my sample size with the de Groot, Poot, and Smit (2010) paper per se. Actually, this article has a larger sample size (seventy studies) than their paper (thirty-one studies).
5. Based on the fact that when I combine all seventy studies together and apply the random effects model, the average effect size is still significantly positive, I believe I am making a good trade-off: The estimated average effect size although has a relatively wide confidence interval, is significantly positive; and the changes different measurements/study level/others make to the estimated effect size can be read off the tables obtained from the mixed effects model.
6. Because most of the time the research and development activities fail and success is rare.
7. Many economic studies suggest that the presence of profits are an important source for innovation investment (Schumpeter 1926; Gilbert and Newbery 1982; Reinganum 1983; Cohen and Levin 1989; Nicholas 2003).
8. Those papers are not included because without further analysis, it is not obvious whether the in-cluster firms and isolated firms are different in terms of innovation (the estimated coefficient is significant in one group and insignificant in another is not sufficient to guarantee the statistically significant coefficient difference across the groups), and of course a meaningful coefficient between clusters and innovation therefore cannot be calculated.
9. For example, for dummy variables, I can recover the standard deviation if the mean is given.
10. Different papers use different significance level, some use 5 percent while some use 10 percent. I define 5 percent as significant in this article, and therefore, I would need an indicator (e.g., *t*-statistics, or asterisks in the results) from the collected studies to tell whether their estimated coefficients are significant at 5 percent level.

11. Results are available upon request.
12. Since most studies contain more than one regression, the total number of regressions is more than the total number of studies. In addition, many regressions use multiple independent variables to measure clustering effects. In this article, every independent variable measuring clustering effects is treated separately as a unique record, with other variables perceived as control variables. Namely, if one regression uses three independent variables to measure clustering effects (such as concentration, localization, and urbanization), three records are obtained out of it. As a result, the total number of records is more than the number of regressions. The interdependence between variables coming from the same regression and the same study is considered later in this article by using certain weighting methods and clustering regression method.
13. The effect size is a standardized magnitude of the relationships between the dependent and independent variables. In this article, it is calculated by two steps. (1) The original estimated coefficients are standardized to be independent of units using the following equation: the standardized coefficient = (the estimated coefficient/ the standard deviation of the dependent variable) * the standard deviation of the independent variable. (2) A standard Fisher's Z transformation is applied to the standardized coefficient. This transformation stabilizes the variance of the coefficient, which is useful in constructing statistics. For more details on the calculations and their applications in the meta-analysis, one can refer to Fisher (1915, 1921), Cheung et al. (2012), and Nieminen et al. (2013).
14. Every record is associated with only one measurement, by definition of record in this article. See note 12 for detail.
15. A regression can report mixed results when it uses different measurements of clustering effects. But since most of the regressions reporting mixed effects are mixed with positive and insignificant effects, the overall clustering effects will add up to be positive.
16. For more discussion on the relevance of the effect size, see Sullivan and Feinn (2012).
17. Per year citation is used rather than total citation, in order not to underrepresent the newly published papers.
18. Since all weights in Table 2 are standardized (the weighted total number of records keeps the same), the weighted average effect size can be directly compared with the unweighted average effect size and across different weighting methods.
19. In most cases, negative binomial or a combination of logistic and Tobit model are more appropriate.
20. The same analysis can be applied to other factors and I just ignore them here to make the explanation relatively simple.

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