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# Establishing open innovation culture in cluster initiatives: The role of trust and information asymmetry

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A R T I C L E I N F O

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A B S T R A C T

Extant research has found superior performance of firms located in clusters. However, it is unclear whether this is based on mere proximity or other unobserved factors. We extend this literature by developing a framework to examine in what way institutions promote open innovation processes between clustered firms. Specifically, we develop a set of hypotheses to investigate to what extent structural and relational elements in a cluster organization affect the open innovation culture. Our model integrates effects of agglomeration, networks, information asymmetries and trust on open innovation culture. We focus on the underlying organizational norms established in clustered firms in relation to open innovation. Specifically, we measure open innovation culture in terms of not-invented- and not-sold-here syndromes, which is facilitated by the integration of trust and reduced by information asymmetry within the cluster region. We test this framework using novel and unique data from member and non-member firms of a cluster initiative in a German high-tech cluster. Our findings from moderation analysis show that a regulatory body in the cluster significantly influences the emergence of both inbound and outbound open innovation activities by member firms in the cluster initiative through increased effects of trust and information asymmetries. Thereby, our paper contributes to literatures of open innovation, including networks of small and medium sized enterprises (SMEs), and cluster policy.

## 1. Introduction

Open innovation has developed as an important research domain and industrial practice to describe "a distributed innovation process based on purposively managed knowledge flows across organizational boundaries" (Chesbrough and Bogers, 2014, p. 17). The literature on open innovation has described many facets of the phenomenon, such as the key concepts and mechanisms that underlie the open innovation process (Dahlander and Gann, 2010; Randhawa et al., 2016; West and Bogers, 2014). However, despite the enormous progress, there is still a large focus on the organization—often *large* organizations—per se as the level of analysis with relatively little attention to other levels of analysis (Bogers et al., 2017; West et al., 2014). In particular, while Chesbrough and Bogers (2014) specifically identify some higher levels of analysis, such as networks and regions, as important research opportunities, they also describe a strong need to better understand intra-organizational attributes of open innovation. In this paper, we address these gaps considering how specific individual, relational and network level characteristics jointly promote open innovation between clustered firms. Thereby, we contribute to the literatures of open innovation and (regulation in) clusters as we show how some of the underlying concepts jointly determine how such boundary-crossing innovation processes can be shaped.

Building on Bogers et al. (2017) we consider multiple levels of analysis as being important to more fully explain certain parts of the open innovation process. Indeed, some scarce work has highlighted the important of considering certain intra-organizational attributes, such as culture (e.g., not-invented-here or not-sold-here) (Antons and Piller, 2015; Herzog and Leker, 2010; Kratzer et al., 2017), information asymmetries (Henkel, 2006), trust (Lee et al., 2010; Perrons, 2009; Rost, 2011), and clusters and geography (Di Minin and Rossi, 2016; Simard and West, 2006). While these studies address important aspects of open innovation, they only address the connections between these elements—e.g., the connection between trust and cluster (Abu El-Ella

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et al., 2015)—to a limited extent. To further explore the relationships and contingencies in this complex set of related concepts, we investigate the question to what extent structural and relational elements in a cluster organization affect the open innovation culture, while also considering some regulatory constraint in terms of cluster membership.

In order to investigate this question, we develop and test a framework regarding the role of trust and information asymmetries for the emergence of open innovation culture among geographically clustered firms with and without membership in a cluster initiative, respectively. In doing so, we create a multi-level perspective on how open innovation culture can be established as well as how a regulatory body (cluster initiative) fosters the emergence of trust in research-intensive industries and its effects on inter-organizational innovation processes.

Building on Chesbrough's (2003) seminal work, and the large body of research on a variety of aspects pertaining to open innovation that has emerged ever since (Dahlander and Gann, 2010; Randhawa et al., 2016; West and Bogers, 2014), this study helps to shed light on the specific relationship across concepts and levels. For example, we build on the notion of information (asymmetries) (e.g. Henkel, 2006) and connect this to trust (Lee et al., 2010; Perrons, 2009; Rost, 2011) in the context of clusters (Abu El-Ella et al., 2015; Di Minin and Rossi, 2016). Interestingly, there has been relatively little research to explicate the role of trust for open innovation, which is somewhat surprising given that open innovation arrangements may often involve less formal contractual measures, hence implying an inherent need for trust-based relationships. This paper contributes to closing this gap with a study of a particularly trust-affine setting from a spatial perspective (Gassmann et al., 2010, p. 213). Using novel and unique data from a cluster region in South-Western Germany, we were able to disentangle geographical effects of proximity from those linked to membership in a cluster organization. Scholars have found external search strategies to be organized in regional systems (Belussi et al., 2010; Cooke, 2016). We extend this literature by differentiating the cluster effect into two components and find that among all firms located in the same region, membership in a cluster initiative increases both inbound and outbound open innovation activities; in other words not-invented-here (Katz and Allen, 1982) and not-sold here (Herzog, 2008) syndromes are decreased for these firms. This innovation process-oriented analysis supports earlier findings (Love et al., 2011), however, we could not differentiate different inbound (sourcing, acquiring) or outbound (revealing, selling) processes (Dahlander and Gann, 2010).

The rest of the paper is organized as follows. We delineate the conceptual background consisting mainly of cluster and network literatures, which is the context in which we analyze the role of information asymmetry and trust. We then develop our hypotheses. In the following two sections we describe our data and measures, before we present corresponding findings from at the structural model level. Finally, we discuss our findings, provide some theoretical contributions and practical implications and conclude with limitations and future research avenues.

## 2. Conceptual development

### 2.1. Open innovation in cluster initiatives

Since behavioural regularities of open innovation, known as outside-in, inside-out and coupled processes (Gassmann et al., 2010, p. 214), might be influenced by contingency and the periphery of the firm, they do not provide proper measures for open innovation. Accordingly, following the definition of Schein, outside-in, inside-out and coupled processes can be interpreted only as artefacts of a firm's open innovation culture (Schein, 2004, p. 25–38). Thus, to measure open innovation in cluster initiatives, we focus on a firm's underlying behavioural norms and basic assumptions: "*To define culture one must go below the behavioral level, because behavioral regularities can be caused by forces other than culture.*" (Schein, 2004, p. 22). In this definition, open innovation culture equals an organizational learning process where successful answers to the environmental challenges are accepted as basic cultural assumptions and transferred to organizational norms within the firm. Schein sees culture as "… *a pattern of shared basic assumptions that was learned by a group as it solved its problems of external adaptation and internal integration, that has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way to perceive, think, and feel in relation to those problems.*" (Schein, 2004, p. 17). Thus, to measure open innovation, we look below the artefact level and focus on the underlying innovation culture in terms of not-invented- and not-sold-here syndrome (Katz and Allen, 1982; Chesbrough, 2003, p. 186). As such, we define open innovation not as process(es), but rather as a variable of organizational culture.

### 2.2. Agglomeration effects in cluster initiatives

According to Malmberg et al. (1996), economic agglomerations in terms of clusters focus on innovation in technology-driven industries (Malmberg et al., 1996). In this context, the evaluation of cluster effects on the emergence of open innovation appears difficult because a counterfactual situation constrains the direct measurement of innovation as a target variable: it is evident that a firm can either be a member or a non-member of a cluster initiative, but never both at the same time. If an average effect of treatment on the treated is measured with the help of target variables when randomization is missing, visible and/or invisible characteristics of firms may bias the results. Therefore, instead of measuring open innovation as a target variable, it makes sense to have a closer look on cause and effects between agglomeration and the formation of open innovation.

Due to increasing complexity, technological innovation relies on the effective and efficient combination of distributed resources and integrative capabilities ever more (Christensen, 2006, p. 45; Yun et al., 2016a). Firms are barely able to allocate all innovation-related assets by themselves. Complexity has rather led to a cumulative interconnectedness of varying players along the innovation process (e.g. Howells et al., 2003, p. 398; Yun et al., 2016b). This trend goes along with an accelerated diffusion of knowledge due to an increasing availability of knowledge and a higher mobility of individuals (Almeida and Kogut, 1999, p. 905). Hence, in terms of sustainability, to maintain or even expand competitiveness, location factors increasingly gain importance beyond a firm's own resources and capabilities (Čirjevskis, 2016; Ketels et al., 2008). To date, scholars have found several underlying reasons which help to explain the positive effects of firm agglomerations.

Firstly, geographical proximity comes along with positive agglomeration effects on the local employment market, enhanced specific infrastructure and spillover effects among the players in clusters (Bell, 2005; Dosi, 1988, p. 1125; Gordon and McCann, 2000, p. 516; Marshall, 1890). Secondly, spatial agglomerations can provide additional benefits in terms of local industry-specific and production-related cost saving potentials based on the interdependence of transaction costs and geographical proximity in formal and stable inter-firm relationships along the value chain (Scott, 1992; Weber, 1929). Thirdly, social networks (Granovetter, 1985; Harrison, 1992) deliver a rationale for the emergence of social capital in geographical proximity. The formation of local communities of interest by the use of strong inter-personal and firm-spanning contacts is leading to similar, if not even more distinctive effects than those of pure agglomeration or formal networks.

Spillover effects as well as specialized infrastructure and job market intensify the interaction between cluster members in terms of cooperation and/or competition (Porter, 2000, p. 258). Cooperations with related or supporting branches in spatial proximity along the value chain support the establishment of conventions and commonly accepted behavioural patterns in informal networks (Bathelt et al., 2004, p. 38). As a result, social interaction increases on an inter-organizational level. Thus, we propose H1:

**H1.** "The more distinctive the agglomeration effects, the more intensive the network activities in a cluster."

Besides positive effects on the degree of network activity in cluster initiatives in general, the distinctiveness of agglomeration effects might also contribute to the information exchange in the cluster initiative. More specifically, the interaction between economically independent parties of related or supporting branches in spatial agglomeration fosters the establishment of conventions and commonly accepted behavioural patterns in informal networks, also known as local buzz (Bathelt et al., 2004, p. 38). Thus, as a consequence of geographic proximity, the exchange between participating organizations increases. Moreover, in a cluster environment, information exchange often takes place at informal occasions and is reinforced by local media, intermediates or universities. As a result, a topic-specific absorptive capacity develops over time (Bell, 2005, p. 288), which comes along with a reduction of hidden information. Beyond that, regular face-to-face-meetings support the reduction of hidden characteristics in networks (Burt, 1992). As a result, spatial agglomeration reduces information asymmetries with regard to the thematic core of the cluster as well as specific information about other cluster players. In line with these arguments, Malmberg and Power (2005) confirmed that agglomeration in cluster initiatives promotes knowledge generation and accumulation. Thus, we propose H2:

**H2.** "The more distinctive the agglomeration effects, the lower the level of information asymmetries in a cluster."

### 2.3. The evolvement of trust in cluster initiatives

The evolvement of trust in clusters is not examined sufficiently to date. Yet, over time, an increasing involvement of cluster members comes along with a homogenization of different perspectives in a cluster (Burt, 2004). Strong ties on inter-organizational and inter-personal level build a high level of alternating dependencies between cluster members on the base of trust (Williamson, 1993; Zaheer and Venkatraman, 1995). Due to repeated interaction during a continuous social interaction, the participating companies become accustomed to each other, which most probably contributes to the evolvement of mutual trust in the long run. Thus, we propose H3:

**H3.** "The more intensive the network activities, the higher the level of trust in a cluster."

### 2.4. Information asymmetry and trust as antecedents to open innovation culture in cluster initiatives

According to principal-agent-theory, information asymmetries can be classified as hidden information and hidden characteristics (Laffont and Martimort, 2002). In networks, strong ties between the members come along with mutual interdependencies and promote the enforceability of sanctions when commonly shared values and norms are not met properly (Coleman, 1988). Moreover, transactions are embedded into the social and structural environment of networks where interpersonal connections account for an intensified social interaction between the network members. Seen from a theory of information asymmetries point of view, the reduction of information asymmetries, classified as hidden information and hidden characteristics (Laffont and Martimort, 2002), takes time and might be costly also. Thus, there might be good reasons to temporarily foster the build-up of hierarchy along the innovation process rather than promoting hybrid organizations and/or market coordination. As a result of high levels of hidden information and hidden characteristics in cluster initiatives, participating companies most probably foster "not-invented-here (NIH)" and "not-sold-here (NSH)" tendencies, leading to rather weak open innovation culture. Thus, we propose H4:

**H4.** "The higher the level of information asymmetries, the weaker the open innovation culture of companies in a cluster."

With respect to potential effects of trust on open innovation processes in cluster initiatives, findings from transaction cost economics might provide a suitable theoretical rationale. More specifically, authors that have integrated trust into transaction cost economics state: "*Thus, trust acts to reduce transaction costs by reducing or eliminating both ex ante and ex post opportunism. Arguing from a pure transaction cost viewpoint, therefore, the presence of trust should be associated with a lower level of hierarchical governance since trust serves as a substitute for hierarchical control.*" (cf. Zaheer and Venkatraman, 1995, p. 379). Hence, seen from the efficiency arguments of transaction cost economics, trust comes along with an intensification of open innovation culture in clusters. Furthermore, in order to foster a culture that promotes rather than inhibits open innovation activities, a continuous information flow of information between networking partners is of utmost importance. Within this respect, formal and informal collaboration competencies form an important organizational asset of cluster members (Eisenhardt and Martin, 2000, p. 1107). However, both formal as well as informal networks between cluster members only flourish in case mutual trust is present. Furthermore, it is well known that both intensity as well as efficiency of information exchange between economic protagonists are positively influenced when a high level of trust is present (Lane et al., 2001). Consequently, with increasing levels of trust between the organizations of the cluster initiative, the intensity as well as the quality of social interaction increases, leading to an innovation-friendly environment on the base of interpersonal and informal contacts. Thus, we propose H5:

**H5.** "The higher the level of trust, the stronger the open innovation culture of companies in a cluster."

### 2.5. The moderating role of cluster initiative membership

We integrate all hypotheses on the supposed effects of firm agglomeration on open innovation culture in a research framework shown in Fig. 1 (below). To explain open innovation as a resulting variable of organizational culture we append the conflictive arguments concerning cause and effect of trust on the one hand and information asymmetries on the other. To carve out the moderating effects of cluster management and to distinguish between geographic and organizational effects in clusters, we introduce cluster management as a stimulus to differentiate between members and non-members of the cluster initiative. As a result, the moderating effect of the stimulus on the emergence of open innovation can be determined. Thus, we propose H6:

**H6a.** "In the cluster region, trust leads to a higher level of open innovation culture for members of the cluster initiative than for non-members of the cluster initiative."

**H6b.** "In the cluster region, information asymmetries lead to a lower level of open innovation culture for members of the cluster initiative than for non-members of the cluster initiative."

## 3. Methodology

### 3.1. Data

We conducted a quantitative survey in a high-tech cluster located in South West Germany. The cluster region was chosen, as the corresponding area and the residing companies are considered as prime example for innovative German companies that are in regular exchange to jointly innovate. Furthermore, the cluster region encompasses a diverse set of industries, and firms of all kind of sizes, both SMEs and MNCs, ensuring a representative sample of the German industrial sector, akin to an open innovation economy system (OIES) (Yun, 2015). Consequently, the cluster region seems to be tailor-made for a

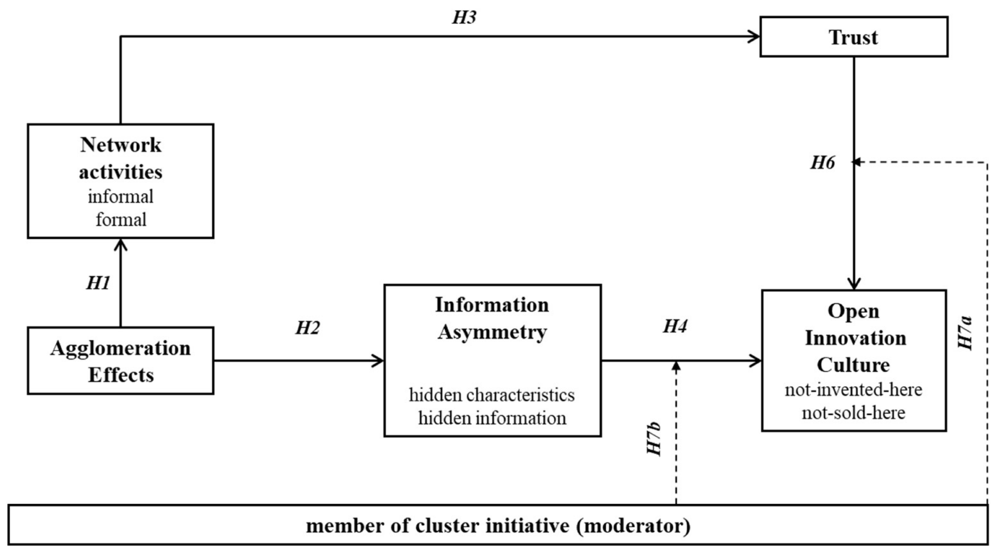


**Fig. 1.** Research framework and hypotheses.

representative, empirical study on open innovation activities in cluster initiatives. The basic population for the survey was constituted by 746 high-tech companies located in the cluster region, consisting of 80 cluster initiative members and 666 non-member firms. The contact addresses were retrieved from the cluster management team, which provided the research team with a database of all companies present in the cluster region. As a result, it was ensured that all relevant companies were contacted, and a representative distribution in terms of company characteristics such as industry, size and sales for the cluster region was established. During the contact process of the companies, only one respondent per company was approached. More specifically, in order to maximize the ability of the respondent to answer the questionnaire items, only members of the management board of the respective company were contacted.

A total of 102 participants completed the questionnaire, representing a return rate of 13.8%, almost evenly split between the members of the cluster initiative with 57 returns and non-members of the cluster initiative with 46 returns. Propensity matching was applied to characteristic items like turnover, R&D quota, number of employees, firm age, target branch, position in value chain and ambidexterity and showed no significant differences between the two groups. Furthermore, a non-response bias test was applied, comparing early and late respondents using a $Chi^2$-test. As late respondent did not significantly differ from early respondents, it was concluded that the returned questionnaires are representative for the target population of the cluster region. We also employed procedural and statistical remedies to minimize and control for the occurrence of common method variance (Podsakoff et al., 2003). As procedural remedy, we clearly separated dependent and independent variables in the questionnaire and tried to keep the items as simple and distinct as possible. As statistical remedy we applied Harman's single-factor test. Since no single factor emerged during an exploratory factor analysis with all independent and dependent variables present, and the first factor only accounted for 38.66% of the variance, we concluded that common method bias should be absent.

The descriptive statistics of the sample turned out as follows. 51% of the respondents were members of the board of directors, 31% held an executive position, 2% were assistants to the chairman, 15% held other positions and 4% did not indicate their position. 255 of the participating companies did belong to the mechanical engineering industry, 19% to the automotive sector, 19% to life science, 17% to electronics, 4 to optical industry, 12% to other industries and 4% did not indicate any industry. With respect to sales the categories turned out as follows: > 250 million € (18%), 250–50 million € (8%), 50–10 million € (17%), 10–2 million € (22%), > 2 million € (23%) and no answer (12%). The distribution of company size was as follows: > 1000 employees (21%), 1000–250 employees (11%), 250–50 employees (24%), 50–10 employees (23%), > 10 employees (14%) and no answers (7%).

### 3.2. Measures

Whenever possible, we used existing scales to measure the constructs of interest. We used five-point Likert-scales ranging from 1 (totally disagree) to 5 (totally agree). In a pilot study, selected network and innovation management experts completed the survey to check for understandability. Small revisions had been made according to the respondents' comments.

We operationalized *agglomeration effects* as reflective construct using 5 indicators that were developed in line with the categories of agglomeration effects introduced by Marshall (1890).

*Trust* was operationalized as formative construct using 3 items, reflecting institutional trust (John, 1984), interpersonal trust (O'Donnell et al., 2008) and intensity of information exchange (Sarkar et al., 2001).

Network activities, information asymmetries and open innovation culture as multidimensional constructs were operationalized as second-order constructs of type two, employing reflective measures at the first-order level and formative measures at the second-order level (Jarvis et al., 2003). As the items at first-order level are a representation of the respective construct, we modeled these items as reflective (Gefen et al., 2000). Contrary, the second-order factors are formed by the sub-dimensions and thus were modeled as formative.

In case of *network activities*, the second-order construct consists of two first-order dimensions: (1) formal network activities measured by one item developed in line with Gordon and McCann (2000) and (2) informal activities measured by four items adapted from Burt (1983).

*Information asymmetries* is formed by two first-order constructs: (1) hidden characteristics measured by five items developed in line with Christensen (1995) and (2) hidden information measured by three items developed in line with Christensen (1995).

The second-order construct *open innovation culture* was operationalized using two first-order constructs: (1) not-invented-here which was measured by 4 items adapted from Mehrwald (1999) and Herzog (2008) and (2) not-sold-here measured by 4 items adapted from Herzog (2008).

The moderating variable *member of cluster initiative* was operationalized as dichotomous variable with 1 = no membership and 2 = active membership.

The focus of our study lies on the relationships between the above described constructs. However, previous studies confirmed that other variables referring to the size and financial situation of companies also affect open innovation culture. We therefore implemented sales, number of employees and R&D investments as controls.

## 4. Analysis and results

As structural equation modeling (SEM) is able to handle many constructs and their interrelations simultaneously, while controlling for measurement error and evaluating measurement validity and reliability (MacKenzie, 2001; Steenkamp and Baumgartner, 2000), we decided to use SEM for our empirical analysis of the relationships depicted in Fig. 1. As formative indicators are necessary for the operationalization of our hierarchical constructs, possible SEM approaches for our statistical analyses are limited to the use of variance-based structural equation modeling (PLS: Partial Least Squares, Chin, 2010).

In order to implement our higher-order constructs, we employed the two-stage approach in PLS. We therefore initially estimated the latent variable scores without the second-order construct being present (Agarwal and Karahanna, 2000; Henseler et al., 2007). Subsequently, we used the latent variable scores as indicators in a separate higher-order structural model analysis.

For the estimation we employed SmartPLS 2.0 (Ringle et al., 2005) using a path weighting scheme for the inside approximation, nonparametric bootstrapping with 1000 replications and individual preprocessing to calculate the standard errors and a mean replacement algorithm to account for missing values (Chin, 1998; Efron and Tibshirani, 1986; Tenenhaus et al., 2005). We proceeded with the evaluation of the measurement and structural model following the recommendations proposed by Anderson and Gerbing (1988). First, the measurement model is evaluated with regard to validity and reliability. Afterwards, the structural model is assessed with regard to main and moderating effects.

### *4.1. Measurement model results*

As all of our implemented hierarchical constructs are modeled with first-order factors as being reflective and second-order factors being formative, we initially assessed indicator and construct reliability as well as convergent and discriminant validity (Churchill and Surprenant, 1982; Götz et al., 2010). We therefore specified a null model with no structural relationships present (Wetzels et al., 2009). Indicator reliability can be confirmed if all indicator loadings are above the threshold value of 0.70 (Chin, 2010). As shown in Table 1, all indicator loadings, except for one item, satisfy this requirement.

For construct reliability we calculated the composite reliability (CR). Table 1 shows that all values for composite reliability exceed the threshold value of 0.70 (Bagozzi and Yi, 1988; Nunnally and Bernstein, 1994). Subsequently, convergent validity of the first-order constructs was assessed by calculating the average variance extracted (AVE; Chin, 1998), which exceeds the minimum recommended value of 0.50 in case of all constructs (Fornell and Larcker, 1981). Since the square root of the AVE also exceeds the intercorrelations of each construct with the other constructs in the model, the Fornell-Larcker criterion is fulfilled in support of discriminant validity (Barclay et al., 1995; Chin, 1998; Fornell and Larcker, 1981; Hulland, 1999). Finally a blindfolding approach was applied to evaluate the predictive validity of each first-order construct (Fornell and Bookstein, 1982). All $Q^2$-values turned out to be significantly different from 0 (see Table 1). Thus predictive validity at first-order level is given (Geisser, 1974; Stone, 1974; Tenenhaus et al., 2005).

We then proceeded with the assessment of the second-order measurement model, which uses latent variable scores as observed indicants for the first-order constructs (Wilson, 2010). First we assessed the significance of all second-order outer weights which indicate the indicators' relative importance in forming the summated scale of the second-order construct (Sarstedt et al., 2009). As shown in Table 2, most significances of the outer weights exceed the critical threshold of $t > 1.98$. Moreover, each weight exceeds the critical threshold of 0.10 (Chin and Newsted, 1999).

Afterwards the variance inflation factor (VIF) was calculated to assess the degree of multicollinearity among the formative indicators (Diamantopoulos and Winklhofer, 2001; Grewal et al., 2004; Henseler et al., 2009). The maximum VIF value among all formative constructs was 1.46, providing assurance that our hierarchical measurement models “network activities”, “information asymmetries” and “open innovation culture” are suitable for further analysis (Henseler et al., 2009).

To conclude, we finally assessed measurement properties of the remaining formative constructs “agglomeration effects” and “trust”. Table 3 shows that for only two indicators a significance at $p < .1$ could be confirmed. However formative indicators should not be excluded from the measurement model and yet each weight except one exceeds the critical threshold of 0.10 (Chin and Newsted, 1999). With respect to the VIF, the maximum value was 1.79, conclusively demonstrating that no multicollinearity should be present (Henseler et al., 2009).

### *4.2. Structural model results*

#### *4.2.1. Main effects*

To test our hypotheses we assessed the path coefficients and their significance levels. All results are depicted in Fig. 2.

The structural model analysis was based on an effective sample size of 102 observations. Overall the estimations fit the data well; the $R^2$ is 0.306, 0.103 and 0.247 for “trust”, “information asymmetry” and “open innovation culture”. A bootstrapping procedure was used to generate t-statistics and standard errors (Chin, 1998). The maximum VIF-value at structural model level was 1.803, indicating the absence of multicollinearity.

In line with Hypothesis 1, agglomeration effects had a significant positive effect on network activities ($\beta = 0.221$, $p < .05$). Contrary to Hypothesis 2, agglomeration effects positively influenced information asymmetry ($\beta = 0.303$, $p < .05$). Furthermore, confirming Hypothesis 3, network activities had a positive impact on trust ($\beta = 0.540$, $p < .01$). In line with our expectations postulated within Hypothesis 4, information asymmetry is negatively related to open innovation culture ($\beta = -0.364$, $p < .01$). Finally, consistent with Hypothesis 5 trust positively affected open innovation culture ($\beta = 0.245$, $p < .10$).

#### *4.2.2. Moderation effects*

In the second phase of our analysis, moderating effects were tested to explore the role of membership of cluster initiative in explaining the relationship between trust as well as information asymmetry and open innovation culture (H6a and H6b in Fig. 1). We used the product term approach to test for possible signs of moderation. Therefore, each item of the independent construct was multiplied with the corresponding item of the moderating construct to form an interaction term (Wilson, 2010). Thereby, all variables were standardized to avoid problems connected to multicollinearity that might arise when generating the product terms (Chin et al., 1996; Low and Mohr, 2001; Ping, 1996).

Supporting Hypothesis 6a, membership of cluster initiative moderates the relationship of trust and open innovation culture by increasing the positive direct effect ($\beta = 0.214$, $p < .10$). Furthermore, consistent with Hypothesis 6b, membership of cluster initiative also moderates the influence of information asymmetries on open innovation culture by increasing the negative direct effect ($\beta = -0.198$, $p < .05$).

## 5. Conclusion

In this study, we extend the literature that explores firm

**Table 1**
First-order hierarchical measurement model results.

| Second-order construct | First-order construct | Item | Loading ($\lambda_i$) | Significance (bootstrapping n = 1000) |
|---|---|---|---|---|
| Network activities | Formal activities | We maintain a lot of contract based cooperations with other firms in the cluster region. | – | – |
| (Burt, 1983; Gordon and McCann, 2000) | CR = 1.000 | | | |
| | AVE = 1.000 | | | |
| | Informal activities | Our staff holds personal contacts to the staff of other firms in the cluster region. | 0.870 | 29.814 |
| | CR = 0.937 | Our staff partially holds contacts to the same employees of other firms in the cluster region. | 0.896 | 44.281 |
| | AVE = 0.787 | Our staff holds contacts to different departments of other firms in the cluster region. | 0.915 | 47.713 |
| | | Our staff holds contacts to different hierarchical levels of other firms in the cluster region. | 0.866 | 27.719 |
| Information asymmetries | Hidden characteristics (r) | We are well informed about the specific capabilities of the staff of other firms in the cluster region. (r) | 0.784 | 16.812 |
| (Christensen, 1995) | CR = 0.929 | We are well informed about the management structure of other firms in the cluster region. (r) | 0.876 | 31.216 |
| | AVE = 0.725 | We are well informed about the product development processes of other firms in the cluster region. (r) | 0.847 | 30.002 |
| | | We are well informed about the strategic cooperations and alliances of other firms in the cluster region. (r) | 0.885 | 41.350 |
| | | We are well informed about the strategic targets of other firms in the cluster region. (r) | 0.861 | 35.539 |
| | Hidden information (r) | We are well informed about the latest technological trends in our business field. (r) | 0.831 | 15.380 |
| | CR = 0.872 | We are well informed about the latest technological trends in adjacent business fields. (r) | 0.863 | 28.607 |
| | AVE = 0.739 | We are well informed about the most important trademarks and patents of other firms in the cluster region. (r) | 0.805 | 32.065 |
| Open innovation culture (r) | Not-invented-here | We rather try to establish new technological know how by ourselves than by means of cooperation. | 0.749 | 11.293 |
| (Herzog, 2008; Mehrwald, 1999) | CR = 0.836 | The allotment of technologies by means of cooperation appears less attractive to us because we would have to disclose our own technological know how. | 0.822 | 19.614 |
| | AVE = 0.563 | | | |
| | | In order to keep our competitive position we must not draw technologies by means of cooperation. | 0.769 | 8.744 |
| | | We would weaken our competitive position if we would draw technologies by means of cooperation. | 0.649 | 6.321 |
| | Not-sold-here | If we license out our technologies, we run the risk of losing control on them. | 0.727 | 9.156 |
| | CR = 0.853 | Our technologies should rather be commercialized by ourselves than by means of cooperation or licensing-out. | 0.806 | 12.895 |
| | AVE = 0.592 | We should have exclusive rights for the use of technologies. | 0.784 | 9.494 |
| | | Our technologies should exclusively be commercialized along our own sales channels. | 0.759 | 12.200 |

**Table 2**
Second-order hierarchical measurement model results.

| Second-order construct | First-order construct | Weights | Significance (bootstrapping n = 1000) |
|---|---|---|---|
| Network activities | Formal activities | 0.631 | 2.567 |
| VIF = 1.196 | Informal activities | 0.561 | 2.269 |
| Information asymmetries | Hidden characteristics | 0.599 | 1.667 |
| VIF = 1.462 | Hidden information | 0.532 | 1.468 |
| Open innovation culture | Not-invented-here | 0.946 | 4.307 |
| VIF = 1.077 | Not-sold-here | 0.157 | 0.674 |

performance in clusters by developing a framework to examine in what way institutions promote open innovation processes between clustered firms. Specifically, we integrate effects of agglomeration, networks, information asymmetries and trust on open innovation culture, and highlight how structural and relational elements in a cluster organization affect the open innovation culture in terms of not-invented- and not-sold-here syndromes. We find that a regulatory body in the cluster significantly influences the emergence of both inbound and outbound open innovation activities by member firms in the cluster initiative through increased trust and reduced information asymmetries. Thereby, our paper contributes to literatures of open innovation, including SME networks, and cluster policy.

### 5.1. Theoretical contribution

The overall research goal of this study was to examine open innovation processes in cluster initiatives. By drawing on past research on inbound and outbound phases of the innovation process (Chesbrough and Bogers, 2014; Dahlander and Gann, 2010; Katz and Allen, 1982), we strived to shed light on how agglomeration effects influence the evolvement of trust and information asymmetries in cluster initiatives as levers to induce or inhibit the establishment of an open innovation culture. We thereby extend current knowledge about clusters and open innovation culture (Eisenhardt and Martin, 2000; Herzog, 2008) by developing a framework to examine, how a regulatory body promotes the emergence of trust-based innovation processes between clustered firms. In doing so, we aim to distinguish between agglomeration effects as trigger of open innovation processes and trust and information asymmetries as resulting antecedents of an open innovation culture.

With respect to agglomeration effects, our results confirmed that agglomeration effects significantly contribute to the degree of network activities of companies in a cluster region, which itself enhances trust between residing companies. This former finding is in line with previous studies, suggesting that spillover effects due to positive agglomeration effects might intensify the interaction between cluster members in terms of cooperation and/or competition (Bathelt et al., 2004; Porter, 2000). The latter finding is consistent with research of Burt (2004) and Williamson (1993) which confirmed that an increasing involvement of cluster members comes along with a homogenization of different perspectives in a cluster, which might promote strong ties on inter-organizational and inter-personal level that are the building stones of mutual trust. Furthermore, our results also deliver first empirical evidence, that agglomeration effects might under certain circumstances, such as cluster regions, also increase rather than decrease information asymmetries between companies. Contrary to previous findings suggesting that agglomeration leads to a topic-specific absorptive capacity (Bell, 2005), which reduces hidden information and hidden characteristics in networks (Burt, 1992), our findings indicate a positive influence of agglomeration effects on information asymmetries in cluster regions. A possible explanation for this contradictory finding might lie in the peculiarities of a cluster region.

With respect to antecedents of an open innovation culture in cluster initiatives, our findings deliver first empirical evidence, that both constructs, namely innovation asymmetries and trust, represent antagonists in establishing a culture that fosters open innovation processes. More specifically, our findings confirm that information asymmetries reduce the evolvement of an open innovation culture. This finding is in line with a study of Coleman (1998), suggesting that information asymmetries promote the probability of potential conflicts due to deviations from commonly shared values and norms, and by that might inhibit open innovation friendly processes. Yet, according to our findings, trust turns out to be a significant facilitator of open innovation cultures. This result is in line with findings from transaction cost economics, suggesting that trust comes along with an intensification of open innovation culture in clusters (Zaheer and Venkatraman, 1995).

In addition to the above mentioned direct effects, our findings also provide further insights into these relationships derived from a dedicated moderation analysis. More specifically, membership in the cluster initiative significantly moderates the emergence of open innovation culture of residential companies. While the membership strengthened negative effects of information asymmetries compared to non-member firms, membership in the cluster initiative increases positive effects of trust on the establishment of an open innovation culture.

### 5.2. Practical implications

Beyond these implications for the advancement of cluster theory, our research shows pioneering practical benefit for all stakeholders of R&D clusters in terms of economic, scientific and political players. To date, practical evidence on the positive effects of cluster management is still absent, although research funding increasingly focuses the implementation of regulatory bodies in cluster regions. Contrary to

**Table 3**
Measurement properties for formative constructs.

| Construct | Indicator | Weights | Significance (bootstrapping n = 1000) |
|---|---|---|---|
| Agglomeration effects | In the cluster region, we find a sufficient number of skilled labour for our business field. | 0.230 | 0.995 |
| (Marshall, 1890) | In the cluster region, the skilled labour in our business field have a high level of qualification. | 0.513 | 1.880 |
| VIF = 1.785 | Our geographic location allows a high level of productivity. | 0.157 | 0.980 |
| | In the cluster region, we benefit from a well developed infrastructure for our business field (customers, provider, services, logistics, …) | 0.213 | 0.924 |
| | It may happen that some of our employees switch to our competitors in the cluster region. | 0.378 | 1.582 |
| Trust | We need less control for cooperations within the cluster region than for cooperations outside the cluster region. | 0.244 | 1.108 |
| (John, 1984; O'Donnell et al., 2008; Sarkar et al., 2001) | We do not provide a trust credit for cooperation partners from the cluster region. (r) | 0.055 | 0.208 |
| VIF = 1.358 | In the cluster region, there is a regular exchange of information between other firms and us (e.g. meetings, workshops, …). | 0.964 | 5.068 |

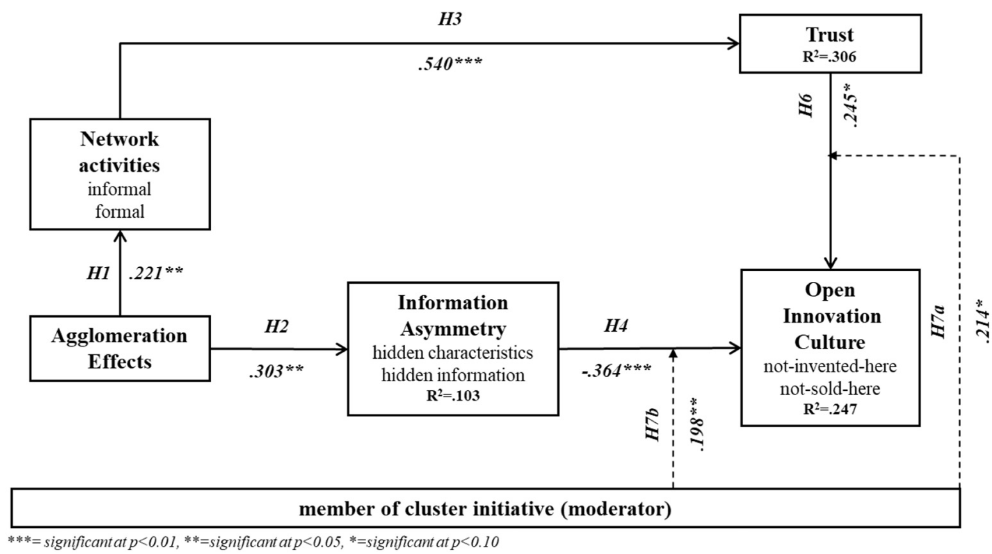


**Fig. 2.** Structural model results.

previous attempts to evaluate the funding of cluster initiatives, we deliver a workaround to the methodologically insufficient determination of mere target variables (e.g. innovativeness, success) in a counterfactual situation. Furthermore, in addition to these improvements for evaluation research and the initiators of funding programmes, our approach enables firms to assess the tangible benefit of (potential) membership in cluster initiatives.

First of all, cluster mangers might use the identified relationships in our research model to promote the evolvement of an open innovation friendly culture in their participating companies. For instance, cluster manager might stimulate the establishment of formal and informal networks by communicating details about local assets in their region. For example, cluster managers could ease the access to skilled labour, logistics or information exchange between different companies.

Furthermore, a dedicated cluster manager might help in orchestrating the social interaction between participating companies on the one side and research institution on the other in a cluster region to establish mutual trust between these actors. Especially, the latter point should strongly contribute to the evolvement of an open innovation culture. Besides rather directly addressing antecedents of open innovation culture in cluster initiatives, it is also of utmost importance to attract and include as much participating organizations as possible since actors are the building stone of successful cluster initiatives especially in research intensive industries. The more innovative assets in the cluster and the better their networking and heterogeneity, the better the national and international competitiveness of the cluster initiative and participating companies will turn out.

From a policy perspective, it might be also fruitful to approach governments in order to achieve an adequate infrastructure in the cluster region that promotes agglomeration effects as trigger of network activities that stimulate trust and by that help establishing an open innovation culture within the companies of the cluster region (cf. Leydesdorff and Ivanova, 2015). On this basis, our work may also contribute to a better integration of open innovation research, practice, and policy (cf. Bogers et al., 2018).

### 5.3. Limitations and further research avenues

The study at hand has advanced our understanding of how an open innovation culture evolves in cluster initiatives. However, the employed design has inherent limitations, that might also constitute interesting future research opportunities.

First, our sample was restricted to German companies. As a consequence, it remains unclear whether the identified relationships also hold when cluster initiatives are employed as research object that are located in other countries. Hence, future studies might gather cross cultural samples that comprise cluster initiatives in different regions and countries to control for potential cultural side effects and thus enhance the external validity of our findings.

Second, distributing our questionnaire with the support of the cluster initiative generated an adequate response rate. Yet, the absolute number of answers was restricted to 102 respondents. While the sample size was sufficient to evaluate the research model and the proposed relationships using component-based structural equation modelling, the moderation analysis was somewhat restricted to evenly distributed cohorts such as the employed membership of the cluster initiative. Future research might strive gathering larger sample sizes of cluster initiatives to test other contextual factors as potential moderating variables and by that enhance the nomological validity of our findings.

Third, we have developed a framework to examine cause and effects between agglomeration, networks and the role of trust for open innovation in R&D-intensive industries. Merging different streams of research, we found that there is no generally valid theory for the emergence of open innovation in clusters, although we were able to confirm fragments of different theories. Therefore, further research on the specific role of trust in a cluster environment is needed. Moreover, the current literature provides a wider number of concepts, such as networks and ecosystems (Adner, 2017; Bogers et al., 2017; Holgersson et al., 2017), for which future research should clarify to overlaps and differences.

Fourth, while we did control for firm size and R&D intensity, we could not capture differences in the increase of open innovation culture stemming from membership in a cluster initiative pertaining to value chain position (Christensen et al., 2005). Relatedly, Yun et al. (2016a) use an agent-based model to identify benefits of open innovation as determined by the stage in industry lifecycle. In industrial clusters there are typically firms throughout the value chain precisely in order to facilitate transactions, yet we find positive effects of organizational membership throughout, thereby corroborating our results, yet opening avenues for further research.

Fifth, this study employed a cross-sectional design, leading to answers on the independent and dependent variable based on answers from the same individual. This procedure might lead to common method variance. In order to alleviate potential problems associated with common method bias both procedural as well as statistical remedies were implemented. While no sign for common method variance could be found, future research might either use a dyadic design or longitudinal data to fully exclude potential problems associated with common method variance.

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