Measuring the effects of intersecting faultline structures on employee absenteeism in Bayesian multiple membership models

Master thesis presented

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ABSTRACT

Building on network theory and more recent advances in diversity research, this paper introduces the notion of intersecting faultline structures to overcome both conceptual and methodological shortcomings of traditional faultline research. In doing so, the paper develops and tests a more rigorous version of Steers & Rhodes' (1978) seminal model of employee attendance behavior, linking group-level faultline structures to individual-level absenteeism. Empirically, the analysis draws on a subset of a large-scale sample from a Swiss service company, covering 2293 employees in 464 organizational units across the country. To account for the non-nested structure of the data, novel Bayesian multiple membership models for organizational count data are employed to assess the effects of intersecting age × gender and age × language faultlines on employee absenteeism. In sum, the empirical results indicate that higher levels of intersecting age × gender faultline structures might correspond to lower levels of voluntary absence behavior. Moreover, the findings support some of the key propositions of the Steers & Rhodes model pertaining to the effects of employees' gender and organizational tenure.

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1. Introduction[1]

Over the past decades, globalization forces and transboundary mobility of employees led to increasingly diverse workforces. In turn, the emerging diversity structures influence organizational outcomes on various levels, including group performance or individual absenteeism as a prominent example of employee withdrawal behavior. In order to develop and implement effective diversity management practices, a deeper understanding of the causes and effects of these compositional dynamics is essential.

Even though this considerable practical relevance is reflected by a growing body of research on organizational diversity, empirical findings on the consequences of diversity structures are mixed (see, e.g., Horwitz & Horwitz, 2007; Van Knippenberg & Schippers, 2007 or Van Dijk, Van Engen, & Van Knippenberg, 2012 for an overview). While the bulk of research focuses on the putative effects of unidimensional diversity characteristics, Lau & Murnighan (1998, 2005) argue that the multidimensional alignment rather than the unidimensional dispersion of demographic diversity structures drives organizational outcomes. Accordingly, specific configurations of demographic attributes within groups evoke so-called *faultlines*, defined as "hypothetical dividing lines that may split a group into subgroups" (Lau & Murnighan, 1998, p. 328). Thus, contrary to diversity research, faultline research focuses on multiple structural dimensions simultaneously. Despite these conceptual advances, however, empirical findings on the interplay of attribute structures remain inconsistent (Thatcher & Patel, 2011).

In view of the above, this paper argues that these inconsistent findings result from a questionable assumption of faultline theory which disregards the precise configurational pattern of intra-organizational diversity structures. Originating in Lau & Murnighan's (1998) seminal work, faultlines imply that congruent structures, i.e., structures where all employees share the same attribute on each dimension, evoke the same effects as completely dissimilar structures. Put differently, faultlines are theoretically expected to yield the same outcomes at minimum and maximum levels of diversity.

[1]Thanks to Florian Kunze for providing access to the data and for helpful comments on this paper. Moreover, I am greatly indebted to Michael Herrmann for inspiring the paper's main argument and, more generally, for offering constructive feedback on a wider range of topics.

The reason is easy to grasp: Since faultline theory builds on the rationale of potential dividing lines between internally homogeneous subgroups, these splits will be largely inexistent when the dispersion of individual attributes is high and absent if group compositions lack attributional variance altogether. Given the above-mentioned empirical findings in diversity research, this prior assumption is unlikely to hold, calling for a more accurate approach to analyzing multidimensional diversity structures by taking the precise configuration of individual attributes into account.

Emphasizing the relevance of social structures ties in with contemporary literature on absenteeism which mainly focuses on group-level predictors of employee absence behavior (e.g., Xie & Johns, 2000; Biron & Bamberger, 2012; Gellatly & Allen, 2012). Surprisingly, analyses investigating the link between faultlines and individual absenteeism have been missing to date. Similarly, current faultline research primarily focuses on the effects of intra-organizational faultlines on group-level outcomes, whereas studies tackling individual-level outcomes are, although promising, still rare (Thatcher & Patel, 2011; Meyer et al., 2014).

This paper attempts to fill the aforementioned gaps by integrating research on individual-level absence behavior and group-level faultline structures. In doing so, it contributes to the re-emerging debate on the contextual predictors of employee absenteeism by developing and testing a more rigorous version of Steers & Rhodes' (1978) seminal model of attendance behavior. Within this theoretical framework, the concept of intersecting faultline structures is introduced. Drawing on the theoretical underpinnings of network theory and relational demography alike, the notion of intersecting faultlines – defined as the degree of structural overlap across distinct attribute dimensions – posits that structural similarity across multiple faultline dimensions reduces voluntary absence behavior by fostering intra-group communication and, thus, group cohesion.

While addressing specific faultline configurations is in line with more recent methodological advances in organizational research (notably Sawyer, Houlette, & Yeagley, 2006; Mäs, Flache, Takács, & Jehn, 2013), this paper differs from existing works in important ways. First, the paper brings together diversity and faultline research by isolating the effects of overlapping unidimensional structures while still taking their interplay into account. Second, contrary to well-established faultline measures such as Thatcher, Jehn, & Zanutto's (2003) *Fau* index, faultlines are operationalized as structural networks connecting employees who share common attributes. This approach allows capturing group structures without making prior assumptions on the configurational alignment of individual attributes. More precisely, instead of presuming a clean split between two or more internally homogeneous subgroups, faultlines are modeled as a structural continuum ranging from completely dissimilar to congruent structures.

In sum, the aim of this paper is twofold. Conceptually, it introduces the notion of intersecting faultline structures by relaxing untested prior assumptions on the attribute configurations underlying organizational faultlines. Empirically, the paper investigates the effects of intersecting age $\times$ gender and age $\times$ language faultlines on employee absenteeism in a novel methodological framework, using Bayesian multiple membership models to account for the non-nested structure of the organizational data in the sample.

2. Theoretical framework and hypotheses

The theoretical framework in this paper builds on Steers & Rhodes' (1978) seminal model of attendance behavior. Being a conceptual model rather than a full-fledged theory, Steers & Rhodes' process model aimed to be as inclusive as possible with regard to the number of predictors. In essence, attendance behavior is modeled as a function of two endogenous predictors, namely, an employee's motivation to attend and an employee's ability to attend. In turn, both motivation and ability to attend are influenced by personal characteristics (e.g., age, sex, tenure, education), job-related characteristics (e.g., job level, work group size) and contextual factors (e.g., economic conditions, work group norms). By drawing a clear distinction between motivation and ability to attend, Steers & Rhodes distinguish between voluntary and involuntary attendance behavior. Provided that an employee has the ability to attend, their motivation to attend turns into the main predictor of attendance.

Over time, Steers & Rhodes' conceptual framework has been subject to criticism as it lacks precision by including predictors relating to different *time frames* for studying absence behavior (Harrison & Martocchio, 1998; Steel, Rentsch, & Van Scotter, 2007). Core criticism is that observed employee absences are monitored – and, thus, aggregated – over fixed time periods. Accordingly, Harrison & Martocchio (1998) advocate what Steel et al. (2007, p. 193) term "predictor-criterion matching" by pairing short-term (proximal), mid-term (medial) and long-term (distal) predictors of absenteeism with their corresponding time frame. Long-term absence frames exceeding 12 months are best predicted by temporally stable predictors, such as demographic characteristics, whereas short-term and mid-term absences up to 12 months are best predicted by more dynamic predictors such as work attitudes and job satisfaction. Steel et al. (2007) demonstrated empirically that long-term employee absences are indeed best predicted by demographic characteristics, supporting one of Harrison & Martocchio's core arguments.

The theoretical framework in this paper integrates Steers & Rhodes' seminal model and its subsequent refinements by modeling long-term (i.e., annual) voluntary absence behavior as a function of individual-level and group-level contextual predictors showing little change within one year.[2] In doing so, both a more parsimonious conceptual framework and an enhanced consistency between theoretical framework and empirical model are achieved.

2.1 Chronological age and absenteeism

In a general sense, given that health deteriorates with increasing chronological age, older employees are more prone to illnesses by nature. Pertaining to voluntary absences, however, the causal mechanism linking chronological age and absenteeism differs considerably.

Following the arguments of Drago & Woodsen (1992), an inverse relationship

[2] Strictly speaking, given the non-nested data structure of the sample, all contextual predictors in the empirical model are employee-specific weighted averages rather than conventional group-level predictors. For simplicity, the respective predictors are still referred to as group-level predictors hereinafter (cf., section 3.3).

between age and voluntary absenteeism is theoretically expected for two reasons. First, younger employees are less bound by location and change jobs more frequently which is reflected by lower levels of organizational commitment compared to older employees. Second, older workers face comparatively lower opportunity costs of missed free time activities. In addition, employees with higher absence rates are generally at risk of getting laid off and older employees might struggle more with finding new jobs than younger employees.

The empirical findings in absenteeism research only partly support these theoretical arguments. While most seminal studies (e.g., Nicholson, Brown, & Chadwick-Jones, 1977; Gellatly, 1995) and meta-analyses (Martocchio, 1989; Hackett, 1990; Ng & Feldman, 2008) suggest a negative relationship between chronological age and voluntary absence behavior, more recent findings question these well-established results (e.g., Bamberger & Biron, 2007; Johns, 2011; Biron & Bamberger, 2012; Diestel, Wegge, & Schmidt, 2014).

Still, drawing on the aforementioned theoretical arguments, this paper adopts the following hypothesis:

H1: Chronological age is inversely related to voluntary absence behavior.

2.2 Gender and absenteeism

Overall, women are expected to exhibit higher absence levels than men for several reasons. An argument frequently raised is that women are more prone to absence behavior because of family and childcare responsibilities such as taking care of sick children (Steers & Rhodes, 1978; Drago & Woodsen, 1992). Beyond this apparent cause, Johns (2003) argues that women hold less fulfilling job positions and are more susceptible to job-related stress, using withdrawal behavior as a coping mechanism. As a closely related consequence, predominant stereotypes further play a role in explaining gender-specific differences in absence levels as one could argue that it might socially be more justifiable for women to be absent from work (Johns & Nicholson, 1982; Patton & Johns, 2007).

Although the theoretical expectations on the effects of gender on voluntary absenteeism are straightforward, prior empirical findings are inconsistent. While some empirical studies (e.g., Johns, 1978; Biron & Bamberger, 2012; Drago & Woodsen, 1992) and meta-analyses (e.g., Lau, Au, & Ho, 2003) report a positive relationship between being female and showing higher levels of absenteeism, other studies do not find gender-related differences in absence behavior (e.g., Farrell & Stamm, 1988; Johns, 2011; Duff, Podolsky, Biron, & Chan, 2015).

In line with the theoretical arguments, this paper proposes a positive relationship between gender and absence behavior:

H2: Being female is positively related to voluntary absence behavior.

2.3 Tenure and absenteeism

Similar to chronological age, an inverse relationship between organizational tenure and voluntary absence behavior is expected. The rationale is twofold. First, senior employees are less prone to absenteeism as organizational commitment is expected to increase with tenure. Second, over time, the fit between an organization and its employees evolves, resulting from dissatisfied employees either leaving the organization or being discharged if they show high absence levels over a longer period (Martocchio, 1989).

Surprisingly, the corresponding empirical findings are mixed as well. More generally, Ng & Feldman (2010) show that higher tenure is inversely related to counterproductive behavior, whereas the study of Diestel et al. (2014) and meta-analyses by Hackett (1990) and Lau et al. (2003) find no association between tenure and absenteeism. Gellatly (1995), Xie & Johns (2000), and Biron & Bamberger (2012), in contrast, find positive effects of organizational tenure on (self-reported) absence behavior.

Following the theoretical reasoning, the hypothesis is as follows:

H3: Tenure is negatively associated with voluntary absenteeism.

2.4 Absence norms and absenteeism

Initially proposed by Hill & Trist (1953, 1955) and Nicholson & Johns (1985), the notion of absence norm or culture – defined as "a [group-level] process that influences members' absence patterns" (Mathieu & Kohler, 1990, p. 217) – posits that an employee's decision to attend work is affected by their immediate social context.

The underlying theoretical reasoning is that members of an organizational unit share common beliefs and perceptions on what is considered an acceptable absence level. As a result, emerging group-level absence norms shape individual absences since employees adopt the observed absence behavior of their respective co-workers (Chadwick-Jones, Nicholson, & Brown, 1982; Rentsch & Steel, 2003; Biron & Bamberger, 2012).

While the hypothesized effects of demographics and job-related characteristics on absenteeism are, in the first place, derived from logical reasoning, the concept of absence norms originates in social information processing theory (Salancik & Pfeffer, 1978) and social cognitive theory (Bandura, 1986) alike. According to social information processing theory, an individual's immediate social context affects his or her attitudes and behaviors by exerting informational social influence through informational cues on co-workers' absence levels and expressed opinions on absences. Individuals then adapt their own absence behavior to act accordingly (Salancik & Pfeffer, 1978; Gellatly & Allen, 2012). Likewise, social cognitive theory suggests that employees reproduce their co-workers' behavior through social learning which, in turn, results from interactions among behavioral, personal, and contextual factors (Bandura, 1986).

Empirical findings strongly support the view that group-level absence norms are positively related to individual-level absence behavior. Among others, Mathieu & Kohler (1990), Gellatly (1995), Xie & Johns (2000), Biron & Bamberger (2012) and Gellatly & Allen (2012) all demonstrate a positive effect of group absence norms on employee absenteeism.

Since both theoretical arguments and empirical findings propose that employees who observe a higher (lower) group-level absence norm will exhibit higher (lower) levels of absence behavior themselves, the hypothesis is as follows:

H4: Group-level absence norms are positively related to voluntary absenteeism.

2.5 Intersecting faultline structures and absenteeism

Building on more recent arguments in faultline research, this paper makes a case for departing from both diversity and traditional faultline theory by investigating the effects of intersecting group-level attribute structures on employee absence behavior.

As briefly stated in the introduction, empirical findings on the effects of intra-organizational diversity differ substantially across studies, depending on the adopted theoretical perspective. On the one hand, social identity theory (Tajfel, 1981; Tajfel & Turner, 1986; Turner, 1987) and the similarity-attraction-paradigm (Byrne, 1971) predict negative effects of demographic diversity on unit-level outcomes, resulting from employees' self-categorization into distinct groups. Information-processing and decision-making theories, on the other hand, expect positive impacts of task-related diversity on group outcomes due to greater variations in group members' skills and knowledge (Van Knippenberg, De Dreu, & Homan, 2004). In other words, demographic diversity is generally assumed to negatively influence organizational outcomes, whereas task-related diversity is often associated with positive outcomes by fostering information- and knowledge-sharing among group members. Irrespective of the substantive differences between social identity and information-processing theories, both competing approaches understand diversity as a unidimensional concept without taking interdependencies between distinct diversity characteristics into account.

In contrast, Lau & Murnighan's (1998) concept of group faultlines emphasizes the multidimensional alignment of diversity characteristics for explaining organizational outcomes. Put briefly, faultline theory posits that (negative) outcomes are driven by the alignment of multiple unit-level diversity characteristics which creates splits between internally homogeneous subgroups and potentially evokes inter-group conflicts. The resulting faultlines differ in strength, depending on the number and configuration of aligned attributes as well as the number of subgroups. If multiple diversity attributes align, faultlines are strong as intra-group homogeneity increases while the number of subgroups is reduced. Conversely, faultlines are weak when attributes misalign since the number of subgroups and, thus, the structural fragmentation within organizational units is higher.

Meyer & Glenz (2013) further highlight the relative importance of Lau & Murnighan's faultline concept by disclosing a major shortcoming of unidimensional diversity research. Despite having the same level of attribute diversity, organizational units can exhibit different levels of faultline strength, depending on the distributional pattern of the respective diversity characteristics. Using Lau & Murnighan's (1998) hypothetical groups, table 1 illustrates this argument. Although groups 3 (5) and 4 (6) are almost equally diverse, faultline strength differs considerably, evoking different levels of conflict potential among group members.

While Meyer & Glenz' argument is justified, the reverse logic applies as well. According to faultline theory, groups 1 and 8 exhibit nearly the same level of faultline strength, even though the level of intra-group diversity differs tremendously. The same holds for groups 4, 6 and 7. In other words, faultline theory assumes that both minimum and maximum levels of diversity evoke the same organizational outcomes, resulting from the lack of attribute variance at minimum diversity and the high structural fragmentation at maximum diversity, respectively (cf., Lau & Murnighan, 1998, p. 331).

Given the above findings in diversity research suggesting that minimum and maximum levels of demographic diversity yield opposing outcomes, this assumption is unlikely to hold. While minimum diversity implies a high level of group cohesion and intra-group communication due to attribute similarities among employees, maximum diversity is assumed to evoke negative outcomes resulting from demographic dissimilarities among employees. Moreover, Thatcher & Patel (2011) demonstrate that gender has a stronger effect on faultline strength than age, although both diversity characteristics are demographic attributes. The situation is further complicated when considering the interplay between demographic and task-related diversity structures.

Table 1. *Lau & Murnighan's (1998, p. 330) hypothetical groups.*

Group	Member A	Member B	Member C	Member D	Diversity	FLS
1	White Male 20 Sales	White Male 20 Sales	White Male 20 Sales	White Male 20 Sales	None	None
2	White Male 20 Sales	White Female 30 Sales	Asian Female 25 Sales	Asian Male 20 Sales	Very low	Weak
3	White Male 50 Plant manager	White Male 55 Plant manager	Black Female 31 Clerical staff	Black Female 35 Clerical staff	Low	Very strong
4	White Male 50 Plant manager	White Female 31 Clerical staff	Black Male 55 Clerical staff	Black Female 35 Plant manager	Low	Weak
5	White Male 60 Plant manager	Asian Female 30 HR manager	White Female 58 Plant manager	Black Male 35 HR manager	Moderate	Strong
6	White Male 65 Plant manager	White Female 35 Plant manager	Asian Female 50 Account officer	Black Male 25 Technician	Moderate	Weak
7	White Male 60 Plant manager	Black Female 20 Plant manager	Black Male 40 Secretary	Asian Female 30 Sales	High	Weak
8	Native American Female 20 Unskilled	White Male 30 Supervisor	Black Female 65 Executive	Asian Male 50 Machinist	Maximum	Very weak

Note: FLS denotes faultline strength.

In addition to the heterogeneous effects of distinct diversity characteristics, different combinations of unidimensional diversity structures create different multidimensional configurational patterns. The reason for this is twofold. First, by construction, the more attribute categories are represented in each diversity dimension, the higher the number of potential subgroups – and, thus, the degree of structural fragmentation – is, which mitigates faultline strength. An example for this is employees' sex which can only be categorized as either female or male, whereas, for instance, race can be classified into multiple and potentially overlapping categories. Second, the precise configurational pattern of multiple attribute structures has another important and often overlooked implication for faultline strength. As discussed by Thatcher & Patel (2012), faultline configurations will differ in settings where attribute alignments are ambiguous (e.g., mixed race or multilingualism), depending on the selected attribute classification.

Similar reasoning underlies Sawyer et al.'s (2006) and Mäs et al.'s (2013) notions of attribute cross-categorization and crisscrossing actors. Both concepts challenge one of the core propositions of faultline theory by demonstrating that faultline strength is reduced in situations where attributes are distributed across potential faultlines. Hence, assuming a clear split between two or more internally homogeneous subgroups is unjustified if an employee shares attributes with members of more than one subgroup simultaneously (Sawyer et al., 2004; cf., Homan, Van Knippenberg, Van Kleef, & De Dreu, 2007b). Likewise, Mäs and colleagues (2013) argue that faultline theory disregards the mediating position of crisscrossing actors – also known as *weak ties* (Granovetter, 1973; 1983) or *bridging social capital* (Putnam, 1995; 2000) across disciplines – who bridge potential faultlines by reducing inter-group dissimilarities due to cross-categorized attributes.

Taken together, it is then the precise configurational pattern of faultline structures rather than the alignment of multiple attributes which drives both group- and individual-level outcomes. Consequently, multidimensional approaches for analyzing organizational faultlines require isolating the varying effects of distinct attribute structures by capturing their alignment without making prior assumptions on the underlying compositional pattern. Given that attribute structures will differ in terms of the number of (potentially overlapping) attribute classifications and crisscrossing actors as highlighted by Sawyer et al. (2006) and Mäs et al. (2013), this issue is of particular importance.

In light of the above arguments, this paper proposes the notion of intersecting faultlines for taking the precise configurational pattern of overlapping structures into account. Departing from traditional faultline theory, intersecting faultlines – defined as the degree of structural overlap between two or more unidimensional faultline structures – thus emphasize the interplay of multiple, albeit unidimensional, attribute structures rather than their overall multidimensional alignment. Put differently, intersecting faultlines capture how (dis-)similar multidimensional faultline structures are without making untested assumptions on the underlying attribute composition.

In line with the theoretical underpinnings of both sociological network theory and relational demography, intersecting faultlines posit that the more similar two or more faultline structures are in terms of attribute compositions, the less employee absenteeism occurs. Stemming from the seminal works of Simmel (1908, 1964) and Lazarsfeld & Merton (1954), the notion of homophily in sociological network theory suggests that associations among demographically similar individuals happen more often than among dissimilar ones. Adapted to organizational settings, employees are more likely to interact with co-workers who exhibit similar attributes which increases within-group communication and cohesion (McPherson, Smith-Lovin, & Cook, 2011). Likewise, relational demography research, which draws on Tajfel and Turner's social identity theory (Tajfel, 1981; Tajfel & Turner, 1986; Turner, 1987) and Byrne's (1971) similarity-attraction paradigm, argues that by classifying themselves into distinct social categories based on observable attributes, employees form the basis for within- and between-group distinctions. While perceived similarities among group members foster interpersonal attraction and liking, between-group dissimilarities impair team functioning and encourage anticooperative withdrawal behavior due to lower group cohesion resulting from infrequent interactions among dissimilar employees (Tsui & O'Reilly, 1989; Tsui, Egan, & O'Reilly, 1992; Avery, McKay, & Wilson, 2008).

The view that attributional similarity across structural dimensions might reduce voluntary absence behavior is supported by empirical findings in relational demography and absenteeism research alike. Tsui and colleagues (1992) were among the first to empirically demonstrate that work unit diversity is inversely related to psychological attachment among group members. Subsequently, Sanders & Nauta (2004) used network data to point out that gender similarity is positively related to team cohesiveness which, in turn, negatively influences short-term absenteeism as a form of anticooperative behavior. Avery, McKay, Wilson, & Tonidandel (2012) extended this line of reasoning by showing that both racioethnic and sex similarity in supervisor-subordinate relationships correspond to lower levels of employee absences.

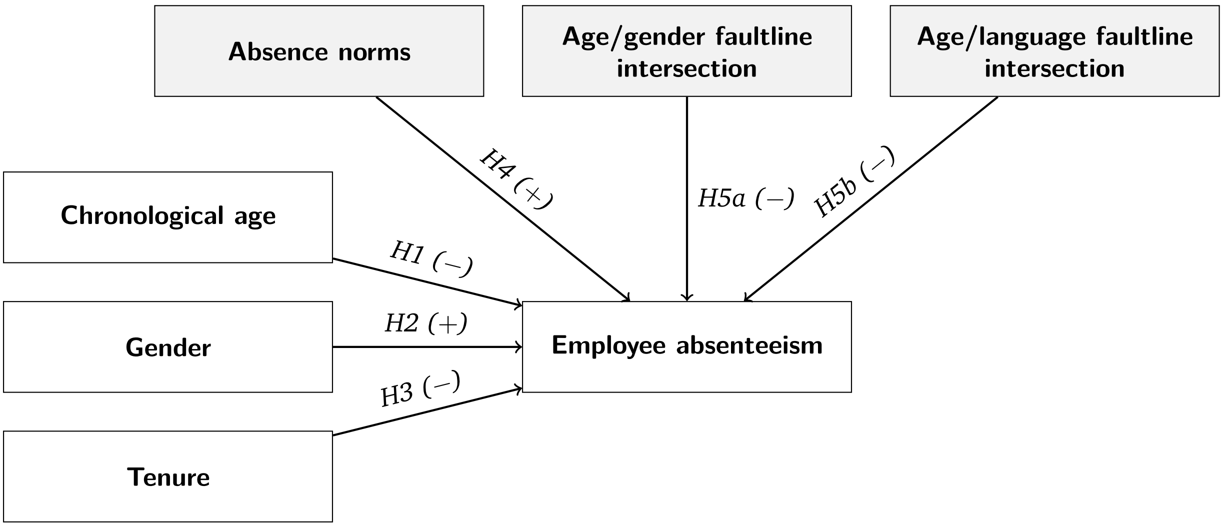
Based on these findings and the above arguments, this paper proposes that demographic age × gender and age × language intersecting faultline structures are negatively associated with employee absence behavior. Hence, bringing together the core theoretical arguments of this section, the hypotheses are as follows:

H5a: Intersecting age × gender faultline structures are inversely related to voluntary absence behavior.

H5b: Intersecting age × language faultline structures are inversely related to voluntary absence behavior.

Figure 1 gives an overview of the conceptual framework adopted in this paper.

Figure 1. *Conceptual model*



3. Methods

3.1 Sample

The empirical analysis relies on an extensive dataset comprising all employees of a large Swiss service company. Data on individual absences, demographics and job-related characteristics were obtained from objective archival company records covering the 12-month period between July 2013 and June 2014.

After removing pseudo-duplicates resulting from intra-organizational job changes, the full sample consists of 18670 employees assigned to 1513 organizational units with 3167 employees being associated with up to four work units.

In total, 245 observations were excluded as they did not fulfill the inclusion criteria for the subsequent analysis for formal reasons. First, work teams are, by definition, composed of at least two employees (Kozlowski & Bell, 2003). Consequently, organizational units consisting of only one employee were removed from the sample. Second, after accounting for sick leaves, employees with less than one remaining work day were omitted since employees cannot exhibit withdrawal behavior when being absent for health-related reasons. However, while not being part of the final sample, the latter observations are included for calculating group-level predictors since they still form part of their respective work team. The same applies to observations which were removed due to missing values on organizational tenure (4 observations).

For computational reasons, the target sample (N = 18425) was reduced to organizational units consisting of 5 to 10 members on employee average only. Of the remaining 2293 employees in the final sample, 32% (68%) of all employees were female (male), had a mean age of 46.36 years (SD = 10.59) and had on average worked 21.32 years (SD = 13.01) for their organization.

3.2 Measures

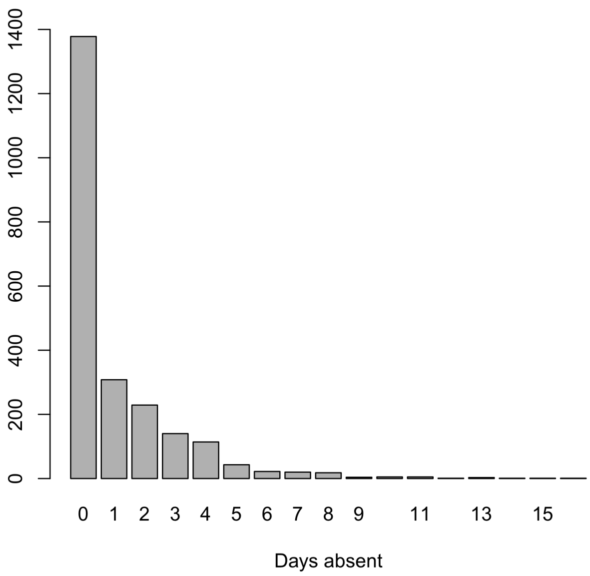
3.2.1 Absenteeism. To maintain consistency between theoretical framework and empirical model, the operationalization of employee absenteeism requires capturing voluntary absence behavior rather than involuntary sick leaves.

This dichotomy is reflected by an ongoing debate on the appropriate measurement of employee absenteeism, originating in the works of Chadwick-Jones, Nicholson, & Brown (1982) and Hackett & Guion (1985). Put briefly, employee absences are commonly measured as either the *frequency* of absences, i.e., the number of times an employee is absent, or total *time lost*, i.e., the sum of days an employee is absent during a fixed time period. While the latter is said to better capture voluntary absenteeism (Steel, 2003), Johns & Al Hajj (2016) – who provide a thorough discussion on this topic – use meta-analyses to show that both measures are, overall, equally reliable.

Irrespective of these findings, the underlying argument is pivotal for deciding on a valid measure. As Johns & Al Hajj (2016) discuss, shorter absences indicate a lack of employee commitment and, thus, better approximate active withdrawal behavior, whereas long-term absences often reflect health-related causes beyond the employees' control.

Following this theoretical reasoning, individual-level absences are measured as the yearly number of work days lost, calculated from each employee's short-term absence hours.[3] This approach yields the advantage of largely ruling out causes of involuntary absenteeism since, for all employees in the sample, short-term absences up to five days did not require medical certificates. In contrast, if this limit is exceeded, employees needed to provide medically confirmed reasons for their absences. For comparability across observations, calculations of absence scores are based on a regular eight-hour working day for both full- and part-time employees.

Figure 2. *Bar graph of absence counts*



[3]Short-term absence measures are not to be confused with the short-term time frames discussed in section 2. While all employee absences in the sample are monitored over a one-year period, relying solely on aggregated short-term absences eliminates sickness absences to a large extent.

As mentioned in the preceding section, each employee's short-term absences were tracked in company records. On average, employees were 1.10 days absent from work (SD = 1.93). As depicted in figure 2, absence data in the sample is highly skewed to the right (skewness = 2.97, kurtosis = 14.59); Section 3.3 discusses the resulting implications.

3.2.2 Demographics and tenure. Data on all individual-level predictors of interest were obtained from company records and remained largely unchanged. Both chronological age and organizational tenure are continuous variables measuring years since birth and years of employment, respectively. Sex was coded as a binary variable taking the value of 1 if an employee is female and 0 otherwise.

3.2.3 Absence norms. Following the seminal work of Mathieu & Kohler (1990), group-level absence norms are commonly approximated as the mean of observed individual-level absence counts within each organizational unit. To further account for varying working hours among employees, absence rates are often calculated by dividing the average number of days absent by the average number of scheduled working days (Xie & Johns, 2000).

Building on the above measures and more recent empirical works in social psychology (e.g., Ostroff, Shin, & Kinicki, 2005; Eder & Eisenberger, 2008; Gellatly & Allen, 2012), this paper employs the so-called *group-minus-me* approach to capture absence norms. Put simply, employee-specific absence rates are calculated by removing each individual's score from the mean score of their corresponding organizational unit. As a result, each organizational unit's absence score differs by employee to better reflect the theoretical notion of employees adopting their co-workers' observed absence behavior.

3.2.4 Intersecting faultline structures. Drawing on the theoretical arguments in section 2.5, faultline structures are operationalized as structural networks where all employees within an organizational unit represent a set of vertices and the shared attributes among them a set of edges. Hence, by adopting a graph theoretical approach to faultlines, each attribute dimension can be captured separately without making prior assumptions on the underlying structural composition. The extent of overlapping faultline structures can be obtained by computing the intersection graph which extracts the intersecting edges (i.e., congruent dyadic ties) across two or more unidimensional attribute structures. Dividing the number of intersecting edges by the number of possible ties to account for the size of an organizational unit then yields the degree of structural overlap across faultline dimensions.

Put more formally, let $G = (V, E)$ be any undirected graph G with vertices V and edges E where $E_{ij} = 1$ if two employees i and j share a common attribute and $E_{ij} = 0$ otherwise. Adopting standard notation, the measure for intersecting faultlines (IFL) can be written as (1)

$$\text{IFL} = \frac{L}{V(V-1)/2} = \frac{2L}{V(V-1)} \tag{1}$$

with L denoting the number of intersecting ties across all dimensions under scrutiny and V denoting the number of employees in each organizational unit. Thus, the measure for intersecting faultlines is the ratio of the number of overlapping structural ties in the intersection graph (L) divided by the number of maximum possible intersecting ties, i.e., $E = V(V-1)/2$ for undirected graphs.[4] The resulting measure ranges from 0 (no common attributes among employees across dimensions) to 1 (all employees share the same attributes on all relevant dimensions).

Taken together, calculating IFL requires five basic steps. (1) Select theoretically sound faultline dimensions which, in principle, can be either demographic, task-related, relational or even cognitive structures, (2) if included, categorize numeric variables, (3) code all dyadic relations among employees for each dimension separately, (4) create the intersection graph to obtain the number of overlapping structural ties, and (5) calculate the measure for intersecting faultlines by dividing the number of overlapping ties obtained in (4) by the number of maximum possible ties in each organizational unit as described above.

For illustration purposes, an example calculation of age $\times$ gender intersecting

[4] Note that the measure for intersecting faultlines is closely related to the concept of network density (see Wasserman & Faust, 1994, chapter 4.2.3 for further information). Moreover, when considering unidimensional faultline structures, the proposed measure conforms to the prevalent measure of network density.

faultlines – based on ten randomly drawn employees from a larger work team in the sample – is shown below. Table 2 reports the required attribute data with team members labeled as employees A-J.

Table 2. *Demographics of randomly chosen subsample (N = 10).*

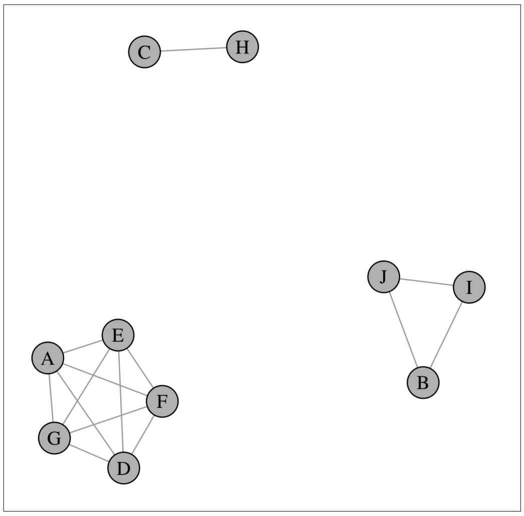
Employee	**Age category**	**Gender**
A	45-55	Male
B	55-65	Female
C	35-45	Male
D	45-55	Male
E	45-55	Male
F	45-55	Male
G	45-55	Female
H	35-45	Female
I	55-65	Female
J	55-65	Female

As the name indicates, data on employees' age and gender are required for calculating the degree of intersecting age $\times$ gender faultline structures. Since chronological age is measured as a continuous variable, ten-year age intervals (up to 25 years, 25-35, 35-45 and so forth) are built, reflecting visible differences in employees' ages. Gender classifications are retrieved from company records. Subsequently, dyadic ties among employees A-D-E-F-G, C-H and B-I-J as well as between members A-C-D-E-F and B-G-H-I-J are coded for obtaining the age and gender graph, respectively. The resulting structural networks are depicted in figures 3a and 3b. Based on these two unidimensional attribute graphs, the intersection graph in figure 3c with ties among members A-D-E-F as well as B-I-J is computed; Employees C, G, and H are unconnected in the intersection graph since they do not share mutual attributes with other employees across dimensions. Finally, the measure for intersecting faultlines is calculated via equation (2)

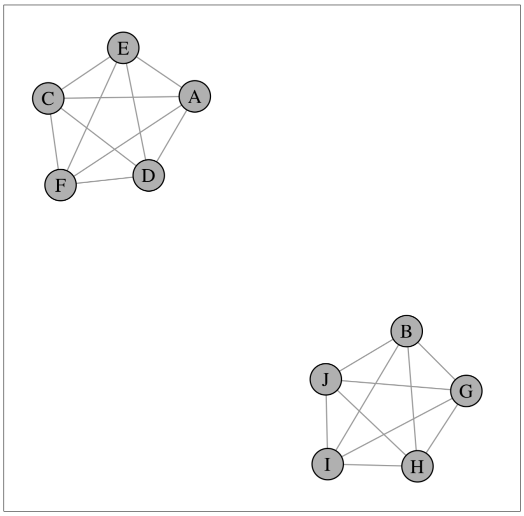
$$\text{IFL} = \frac{2 \times L}{V(V-1)} = \frac{2 \times 9}{10(10-1)} = \frac{18}{90} = 0.2 \qquad (2)$$

The same procedure is applied to calculate the degree of overlapping age $\times$ language of communication faultline structures. For the latter, information on each

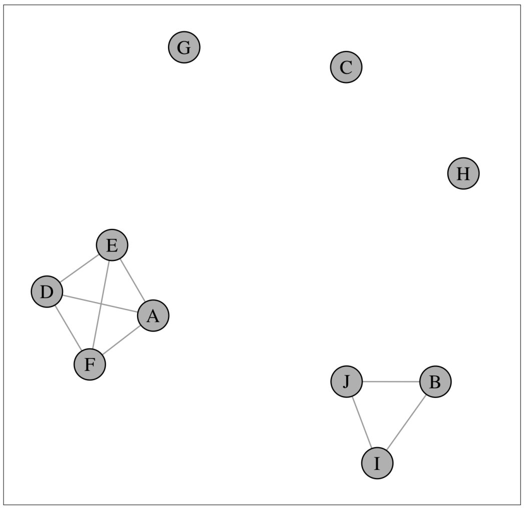
Figure 3. *Age, gender and intersecting faultline structures*



(a) *Age faultline structure*



(b) *Gender faultline structure*



(c) *Intersecting age × gender faultline structures*

employee's classification is obtained from archival records as well. In the sample, three categories are present (German, French, Italian), reflecting Switzerland's tripartite linguistic division.

3.2.5 Control variables. In addition to the predictors of main interest, the following variables are also included to control for alternative explanations.

On the individual-level, two task-related predictors are added. First, prior studies indicate that blue-collar workers are more absent due to higher physical strain and a less flexible work schedule (e.g., shift work) compared to white-collar workers (Chadwick-Jones et al., 1982; Drago & Woodsen, 1992). However, one counterargument against this predominant view might be that blue-collar workers are indeed more absent in the aggregate due to health-related reasons but white-collar workers are psychologically more affected. In this paper, occupations are coded based on each employee's job description in the company records (see the attached replication data for details). Likewise, holding a leading position might be inversely related to voluntary absenteeism since higher job levels are both more satisfying and come along with more responsibilities towards subordinates (Steers & Rhodes, 1978). Hence, a dummy variable indicating if an employee occupies a leading position is included.

Lastly, the number of employees in each work team as calculated from company records is added as a group-level control to account for Steers & Rhodes' (1978) and Porter & Lawler's (1965) argument that increased team size leads to higher voluntary absence behavior due to lower job satisfaction and intra-group communication. Moreover, an individual employee's performance is relatively more important in smaller work teams and, thus, more closely monitored. Consequently, absent employees face a higher risk of being discharged which might reduce absence behavior (Nielsen, 2008).

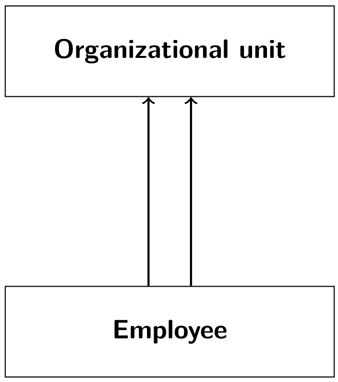
3.3 Analytical procedure and model specification

To test the above hypotheses, overdispersed Poisson multiple membership models are employed. The reason for adopting this modeling strategy is twofold.

First, the number of days employees are absent over a fixed time period are counts which require appropriate regression models as linear (OLS) modeling assumptions are violated (Coxe, West, & Aiken, 2009; Cameron & Trivedi, 2013). This is evident from both absenteeism (Bamberger & Biron, 2012; Duff et al., 2015) and presenteeism research (Bacharach, Bamberger, & Biron, 2010; Johns, 2011) as well as organizational behavior studies in general (see Blevins, Tsang, & Spain, 2015 for an overview) where regression models for count outcomes are increasingly applied. Accordingly, a Poisson model is used for the subsequent analyses. Since Poisson models assume equidispersion, an overdispersion parameter is added to account for unobserved heterogeneity of the observations (Gardner, Mulvey, & Shaw, 1995).

Second, as stated in section 3.1, 3167 (412) observations in the full (reduced) sample are associated with up to four organizational units simultaneously, yielding a non-nested multiple membership structure. Contrary to traditional hierarchical models in organizational research (e.g., Bryk & Raudenbush, 2002; Bliese, Chan, & Ployhart, 2007; Hitt, Beamish, Jackson, & Mathieu, 2007), multiple membership models are used when lower level units, i.e., employees, are members of more than one higher level classification unit at the same time (Browne, Goldstein, & Rasbash, 2001; Rasbash & Browne, 2008; Leckie, 2013). Modeling organizational multiple membership structures then reflects the notion that employees are exposed to varying degrees of group-level influences while attending work. In other words, the more time employees spend in each organizational unit they belong to, the more influence the respective group-level predictors exert on employees' absence behavior. Figure 4 displays the corresponding multiple membership classification diagram.

Figure 4. *Two-level multiple membership classification diagram*



To account for this multiple membership structure, all fixed group-level predictors and controls (absence norm, intersecting faultline structures, team size) are weighted by an employee's actual attendance time in each assigned organizational unit, approximated by subtracting total time absent from target hours.

The same rationale applies for the random effects. Although essential group-level predictors are included in the model, correlated absence scores within organizational units are still expected due to reasons not captured by these fixed contextual effects. First and foremost, organizational units in the sample are located all over Switzerland. Consequently, geographic conditions (e.g., accessibility of the workplace, public transportation problems) as well as regional characteristics (e.g., unemployment rates, rental prices, cultural norms) influence both employees' short-term ability and decision to attend work. Moreover, team-specific differences in working conditions beyond blue- vs. white-collar occupations, such as shift work or flexible work hours, are likely.

In addition, an exposure term is included in the model, indicating that some employees have a higher risk of showing voluntary absence behavior than others. Recall that the sample consists of both full- and part-time employees whose differences in target hours need to be accounted for when modeling absence counts. Furthermore, the exposure term needs to capture an employee's ability to attend work by removing health-related absences from each employee's target scores. Put differently, the amount of time an employee could potentially *decide* to be absent after controlling for long-term sick leaves serves as the exposure time in the model.

Adopting the classification notation of Browne et al. (2001), the resulting two-level multiple membership model in its log-linear form can be written as follows:[5]

$$log(\text{days absent}_i) = log(\text{exposure}_i) + \beta_0 + \beta_1\text{age}_i + \beta_2\text{gender}_i +$$
$$\beta_3\text{tenure}_i + \beta_4\overline{\text{absence norms}}_{2i} + \beta_5\overline{\text{age} \times \text{gender faultlines}}_{2i} +$$
$$\beta_6\overline{\text{age} \times \text{language faultlines}}_{2i} + \sum_{j \in \text{Org. unit}(i)} w_{i,j}^{(2)} u_j^{(2)} + \epsilon_i$$

$$\beta \sim N(0, \sigma_\beta^2) \quad u^{(2)} \sim N(0, \sigma_{u^{(2)}}^2) \quad \epsilon \sim N(0, \sigma_\epsilon^2) \tag{3}$$

where i with elements $i = \{1, ..., n\}$ indexes the lower-level employee classification and j with $j = \{1, ..., J\}$ indexes the higher-level organizational unit classification. Correspondingly, *organizational unit(i)* is the set of work teams j each employee i be-

[5]For brevity, controls are omitted in the equation. By convention, subscripts and superscripts for the lower-level classification units are omitted as well.

longs to. $w_{i,j}^{(2)}$ is the assigned weight w of organizational unit j for employee *i* with

$$\sum_{j \in \text{Org. unit(i)}} w_{i,j}^{(2)} = 1 \text{ for each } i \tag{4}$$

, i.e., all weights sum to unity; $u_j^{(2)}$ denotes the corresponding random effects for each organizational unit.

As stated above, all group-level predictors are attendance-weighted averages and thus differ by the time an employee spent in each organizational unit he or she is associated with. Again, all weights sum to 1 so that, for instance,

$$\overline{\text{age} \times \text{gender faultlines}}_{2i} = \sum_{j \in Org.unit(i)} w_{i,j}^{(2)} \text{age} \times \text{gender faultlines}_{2j}^{(2)} \tag{5}$$

For model estimation, simulation-based Markov chain Monte Carlo (MCMC) algorithms are employed to obtain joint posterior probability distributions using Gibbs sampling (Geman & Geman, 1984). Despite the advantages of Bayesian methods over frequentist approaches (see, e.g., Kruschke, Aguinis & Joo, 2012 for details), the estimation strategy is primarily motivated by the non-nested structure of the organizational data which cannot be easily implemented using maximum likelihood estimation (MLE) as MLE fails to converge due to the rather complex weighting structure of the random components in (3).

Accordingly, an objective Bayesian perspective is adopted by choosing non-informative prior distributions (i.e., priors without incorporating subjective information) for all unspecified parameters in the model. Given the reasonably large sample size, Bayesian results can then be expected to be similar to those obtained by MLE. Detailed information on all prior specifications can be obtained from the replication data.

Data management, visualizations and statistical analyses were carried out in R version 3.2.3 (R Core Team, 2016). All packages used are listed in the references. Additionally, Bayesian data analysis via MCMC sampling was conducted in JAGS version 4.2.0, using the *rjags* package as an interface with R (Plummer, 2003; 2015). MCMC estimation was implemented by running three Markov chains for each model with 300000 iterations, 20000 burn-ins per chain and a thinning interval of 8 to reduce sample autocorrelation.[6] The samplers' initial values were generated automatically, implying that the Markov chains started from the same values. MCMC output analyses and convergence diagnostics were performed using the *coda* package (Plummer, Best, Cowles, & Vines, 2006).

4. Results

4.1 Descriptive statistics

Means, standard deviations, and zero-order correlations for all study variables are displayed in table 3.[7] The bivariate results indicate that, as proposed by hypotheses 1 and 3, both age ($r = -0.17$, $p < 0.001$) and tenure ($r = -0.11$, $p < 0.001$) are inversely related to voluntary absence behavior. Unlike hypothesized (H2), gender is not significantly associated with absenteeism ($r = -0.04$, $p > 0.05$). The same applies to hypothesis 4 which indicates that employees who observe higher levels of co-workers' absences do not decide to stay away more often ($r = 0.03$, $p > 0.05$)

Regarding the variables of main interest, namely, age $\times$ gender and age $\times$ language intersecting faultline structures, the bivariate findings are mixed. In line with hypothesis 5b, the results indicate that age $\times$ language intersections are inversely related to absenteeism ($r = -0.05$, $p < 0.05$), whereas – contrary to hypothesis 5a – age $\times$ gender faultlines are only marginally associated with voluntary absence behavior ($r = 0.04$, $p = 0.05$). Irrespective of the significance levels, however, both effect sizes are rather small.

With respect to the controls, the findings also differ. While team size is not significantly related to individual absence behavior ($r = -0.03$, $p > 0.05$), the bivariate correlations suggest that pursuing white-collar occupations is positively associated with absenteeism ($r = 0.10$, $p < 0.001$), pointing towards the counterargument of

[6] Grand-mean centering of the predictors and parameter blocking as recommended by Gelman & Hill (2007, chapter 19.3) and Jackman (2009, chapter 6.4.2), respectively, did not speed up convergence of the sampler.

[7] As is common practice in organizational psychology, Pearson correlations are employed. To further account for the discrete nature of count data, Spearman's rank correlation coefficients (ρ) are reported in the appendix.

Table 3. *Means, standard deviations, and intercorrelations (Pearson) of study variables (N = 2293)*

Variables	Mean	SD	Correlations 1	2	3	4	5	6	7	8	9	10
1. Absenteeism	1.10	1.93	—									
2. Age	46.36	10.59	−0.17***	—								
3. Gender (0 = male; 1 = female)	0.32	0.46	−0.04	−0.09***	—							
4. Tenure	21.32	13.01	−0.11***	0.65***	−0.37***	—						
5. Absence norms	0.04	0.04	0.03	0.04	−0.02	0.03	—					
6. Age × gender faultlines	0.18	0.11	0.04	0.10***	−0.13***	0.09***	−0.10***	—				
7. Age × language faultlines	0.28	0.13	−0.05*	0.15***	0.05*	0.07***	−0.07***	0.72***	—			
8. Team size	8.63	2.37	−0.03	0.01	0.03	−0.06***	0.06**	−0.12***	0.01	—		
9. Occupation (0 = blue collar; 1 = white collar)	0.36	0.48	0.10***	−0.11***	−0.01	0.03	−0.13***	0.10***	−0.10***	−0.39***	—	
10. Lead (0 = no lead; 1 = lead)	0.10	0.30	−0.04*	−0.04*	−0.16***	0.10***	0.03	0.00	0.00	0.02	0.07***	—

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

white-collar workers being more absent due to psychological strains. Finally, as expected, holding a leading position is inversely related to voluntary absence behavior (r $= -0.04$, $p < 0.05$).

4.2 Estimation results

As stated above, the aim of Bayesian inference is to estimate posterior probability distributions conditional on the observed data. For summarizing quantities of interest from the resulting posterior distributions, point estimates (e.g., posterior mean or median) and interval estimates (e.g., 2.5% and 97.5% percentiles) can be computed. For the latter, the corresponding credibility interval (CI) is obtained by $\alpha - \%$ which – simply put – is the Bayesian equivalent to confidence intervals used in frequentist approaches. Contrary to frequentist approaches, however, no null hypothesis significance testing is performed. Instead, Bayesian analyses allow evaluating whether the model parameters, conventionally denoted by θ, are inside the CI with a certain probability. In other words, it can be assessed whether, for instance, the 95% CI covers the true θ with a probability of 95%, given the data in the sample. Jackman (2000) or Zyphur & Oswald (2015) provide concise introductions on this matter.

Point estimates and 95% credibility intervals for all parameters of interest are reported in table 4 with the corresponding rate ratios and percentage changes displayed in table 5. Density plots for the posterior distributions of the main parameters are depicted in figure 5.

As can be seen in Model 1 on the left part of table 4, the multivariate estimation results indicate that the parameter θ_1 associated with employees' chronological age lies inside the 95% credibility interval [-0.001; 0.02] with an estimated posterior mean of 0.01.

Recall that for the Poisson model in (3), changes in θ_1 pertain to differences in the logs of predicted absence counts per scheduled working days. Accordingly, for a one year increase in chronological age, the differences in the logs of predicted absence counts are expected to increase by $\theta_1 = 0.01$. When exponentiating θ_1, the *incident rate ratio* for a one year increase in age can be obtained (see, e.g., Long & Freese, 2001,

Table 4. *Summary of posterior parameter distributions of study variables*

	Model 1: Main effects				*Model 2: Controls*			
Parameters	Mean	2.5% Percentile	Median	97.5% Percentile	Mean	2.5% Percentile	Median	97.5% Percentile
θ_1 Age	0.01	−0.001	0.01	0.02	0.01	−0.003	0.01	0.02
θ_2 Gender	0.33	0.10	0.33	0.57	0.31	0.07	0.31	0.56
θ_3 Tenure	−0.02	−0.03	−0.02	−0.01	−0.02	−0.03	−0.02	−0.01
θ_4 Absence norms	−60.33	−67.40	−60.53	−52.16	−59.66	−67.02	−59.79	−51.41
θ_5 Age × gender faultlines	−4.28	−8.57	−4.24	−0.01	−3.60	−7.95	−3.53	0.47
θ_6 Age × language faultlines	1.48	−2.36	1.46	5.40	0.93	−2.51	0.93	4.59
θ_7 Team size					0.04	−0.05	0.04	0.13
θ_8 Occupation					−0.51	−0.93	−0.51	−0.11
θ_9 Lead					−0.20	−0.51	−0.20	0.12
DIC	8097				8098			

Note: Intercepts and random effects parameters not reported.

chapter 7.2 for interpretation details). Hence, the exponentiated posterior means indicate the factor changes in the rate of being absent, i.e., for a one year increase in age, the predicted number of absence days is multiplied by $e^{\theta_1} = 1.01$. Correspondingly, a percentage change of $100 \times (e^{\theta_1} - 1) = 1.01\%$ in the predicted absences is expected. Irrespective of these findings, the estimated credibility interval for θ_1 contains zero, objecting hypothesis 1 which proposes a negative relationship between employees' chronological age and voluntary absence behavior.

Table 5. *Incident rate ratios and percentage changes of posterior means*

	Model 1: Main effects		*Model 2: Controls*	
Parameters	e^{θ}	$100 \times (e^{\theta} - 1)$	e^{θ}	$100 \times (e^{\theta} - 1)$
θ_1 Age	1.01	1.01%	1.01	1.01%
θ_2 Gender	1.39	39.10%	1.36	36.34%
θ_3 Tenure	0.98	−1.98%	0.98	−1.98%
θ_4 Absence norms	0.00	−100.00%	0.00	−100.00%
θ_5 Age × gender faultlines	0.01	−98.62%	0.03	−97.27%
θ_6 Age × language faultlines	4.39	339.29%	2.53	153.27%
θ_7 Team size			1.04	4.08%
θ_8 Occupation			0.60	−39.95%
θ_9 Lead			0.82	−18.13%

As expected, the parameter θ_2 corresponding to the effects of an employee's gender has an estimated posterior mean of 0.33 [0.10; 0.57]. Thus, in line with hypothesis 2, the difference in the log of expected absences is 0.33 higher for women than for men. In other words, being female increases the predicted number of days absent by a factor of $e^{\theta_2} = 1.39$ and $100 \times (e^{\theta_2} - 1) = 39.10\%$, respectively.

The estimated posterior mean associated with employees' tenure is consistent with hypothesis 3, positing a negative relationship between organizational tenure and voluntary absences with $\theta_3 = -0.02$ and the 95% credibility interval being [−0.03; −0.01]. Thus, for a one year increase in tenure, the predicted number of days absent decreases by a factor of $e^{\theta_3} = 0.98$ (i.e., $100 \times (e^{\theta_3} - 1) = -1.98\%$).

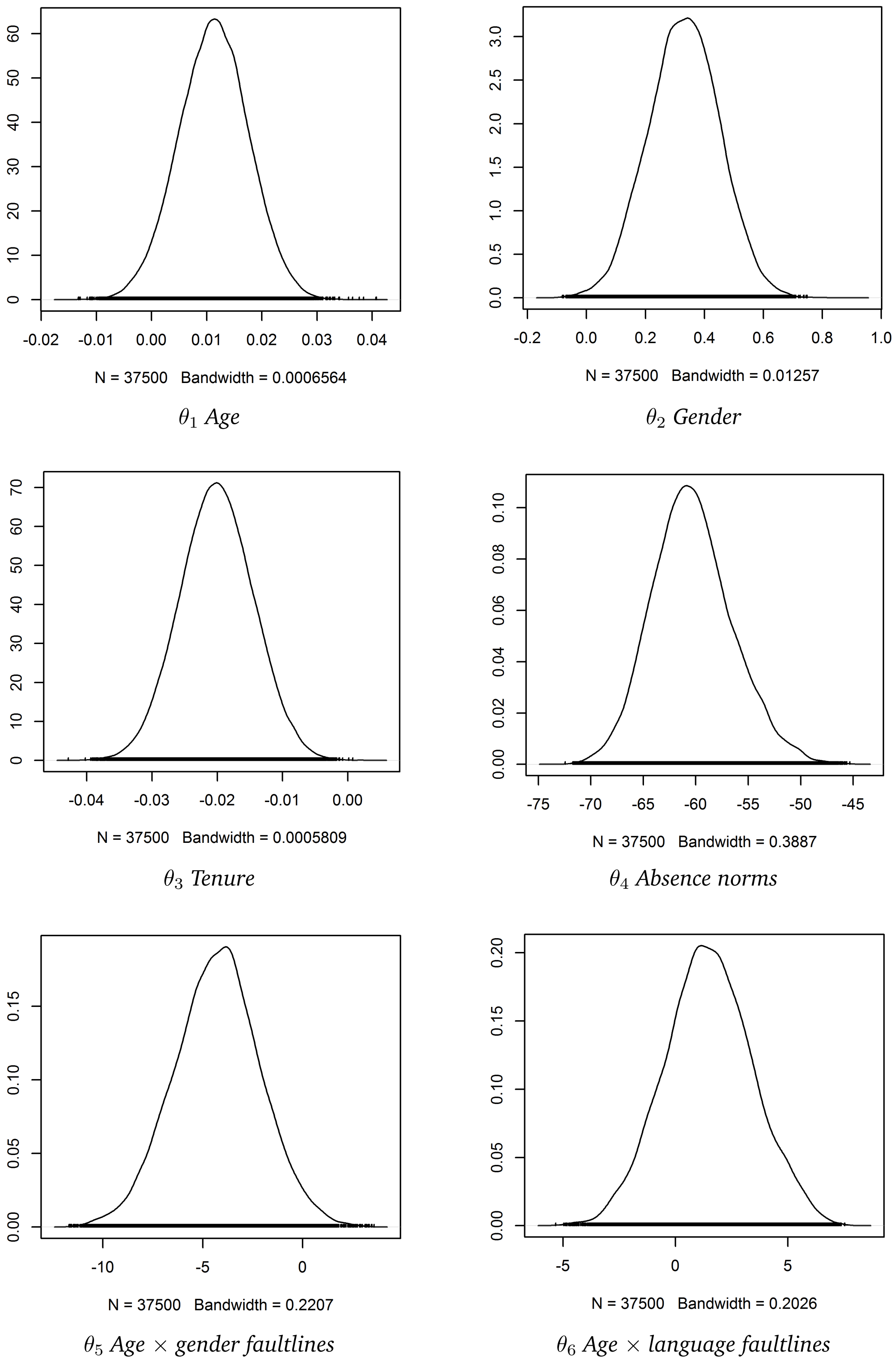
In contrast, θ_4 has a posterior mean of −60.33 with the 95% CI for the effect of absence norms on the logged number of days absent not containing zero [−67.40; −52.16]. Hence, when absence norms increase by one unit, the corresponding rate for the predicted number of days absent changes by a factor of $e^{\theta_4} = 0.00$, contradicting hypothesis 4. One possible explanation for this finding could be the Swiss work culture which might contribute to Swiss employees feeling obliged to cover for absent co-workers.

With respect to the parameters of main interest, θ_5 and θ_6, the multivariate findings are mixed. First, the results indicate that for a one point increase in age $\times$ gender intersecting faultlines, the differences in the logs of predicted absences per scheduled working days are expected to decrease by -4.28 [-8.57; -0.01]. Exponentiating θ_5 then yields a factor change in the rate of being absent of 0.01 when age $\times$ gender faultlines increase by one unit. Correspondingly, absence counts decrease by 98.62% for a one unit increase in age $\times$ gender faultlines, providing an empirical basis for hypothesis 5a. Contrary to these findings, the 95% CI for age $\times$ language intersecting faultlines with an estimated posterior mean of $\theta_6 = 1.48$ contains zero [-2.36; 5.40]. Hence, hypothesis 5b is not supported by the data. To a certain extent, however, the latter might be attributed to differences between hypothetical and actual faultline structures as the Swiss often speak several languages.

In the right part of table 4, the results for the control model (Model 2) are reported. For θ_1 (age), θ_2 (gender), θ_3 (tenure), θ_4 (absence norms) and θ_6 (age $\times$ language faultlines), the posterior means remain largely consistent with Model 1. Substantial changes occur for θ_5 (age $\times$ gender faultlines) with an estimated posterior mean of -3.60 and zero now falling inside the 95% credibility interval [-7.95; 0.47].

Regarding the effects of the controls, the 95% CI for θ_7 (team size) contains zero as well [-0.05; 0.13]. The same applies to holding a leading position (θ_9) with a posterior mean of -0.20 [-0.51; 0.12]. In contrast, θ_8 associated with employees' occupation has an estimated posterior mean of -0.51 lying within the 95% credibility interval of [-0.93; -0.11]. Accordingly, the difference in the log of expected absences per working days is -0.51 lower for white-collar workers than for blue-collar workers. Holding a white-collar occupation thus changes the predicted number of days absent by a factor of $e^{\theta_8} = 0.60$, corresponding to a 39.95% decrease in voluntary absences.

Figure 5. *Posterior parameter distributions of main effects*



θ_1 *Age*

θ_2 *Gender*

θ_3 *Tenure*

θ_4 *Absence norms*

θ_5 *Age* $\times$ *gender faultlines*

θ_6 *Age* $\times$ *language faultlines*

For model comparison, the Bayesian counterpart of *Akaike's information criterion* (AIC), the *deviance information criterion* (DIC) by Spiegelhalter, Best, Carlin, & Van der Linde (2002), is computed with smaller values indicating better model fit to the data. As reported in table 4, the main effects model has a marginally lower DIC and is thus preferred to the control model. Aside from the poorer model fit, the empirical results of the control model should be interpreted with some caution as parameter convergence was – compared to the first model – slightly weaker due to the increased graph size.

5. Discussion

The main objective of this paper was to develop and test a more rigorous version of Steers & Rhodes' (1978) seminal model of employee attendance behavior, linking group-level intersecting faultline structures to individual-level absenteeism. In doing so, intersecting faultlines were operationalized as the overall degree of overlapping dyadic ties across attribute dimensions. To test the hypothesized relationships, Bayesian multiple membership models were employed, using objective archival data on 2293 employees in 464 work units from a large Swiss service company. In a nutshell, the empirical results indicate that higher levels of organizational tenure and observed absence norms correspond to lower absence levels, whereas being female is positively associated with absenteeism. In contrast, the findings on the putative effects of intersecting faultlines are mixed, suggesting that age $\times$ gender but not age $\times$ language faultline structures might be inversely related to voluntary absence behavior.

Empirically, the findings in this paper contribute to both the re-emerging works on group-level predictors of employee absenteeism and faultline research. Broadly speaking, the results demonstrate that the well-confirmed positive relationship between absence norms and voluntary absence behavior does not hold in certain organizational settings and, thus, cannot be generalized unconditionally (cf., section 2.4). Similarly, the mixed results on the effects of intersecting faultlines imply that investigating multidimensional attribute structures is indeed necessary but might not suffice for providing conclusive answers on potential consequences of intra-organizational faultlines. Chances are that these findings – at least to a certain degree – result from adverse effects between attribute similarities across dimensions and reinforcing faultlines. While this paper makes a case for the positive effects of structural *similarity*, traditional faultline theory and, closely related, crosscutting theory (e.g., Blau & Schwartz, 1984) emphasize the positive effects of structural *dissimilarities* whenever multiple attributes crosscut. However, rather than being mutually exclusive, it is more likely that both theoretical rationales have a joint impact on outcomes, indicating that further structural characteristics, such as the number of subgroups or the degree of structural fragmentation, might be pivotal. Nevertheless, the mixed findings in this paper cast doubt on empirical approaches that do not isolate the effects of distinct faultline structures.

From a methodological perspective, the proposed graph theoretical operationalization of faultlines offers significant advantages over existing measures (see Thatcher & Patel, 2012 and Meyer et al., 2014 for excellent overviews). First and foremost, no unjustified restrictions on the number, size or configurational pattern of faultlines are imposed. Instead, faultline structures are determined by the observed attributes and, in settings where unidimensional structures are either congruent or lack attribute variance altogether, no 'artificial' faultlines are induced. In contrast, faultline measures based on multivariate cluster analyses – for instance, the widely used *Fau* index by Thatcher et al. (2003) and, subsequently, Bezrukova, Jehn, Zanutto, & Thatcher (2009) – require forming subgroups even if this prerequisite is not satisfied empirically. Additionally, both overlapping memberships (i.e., cross-categorizations) and crisscrossing actors can be captured by graph theoretical approaches. Operationalizing faultlines as structural networks further allows identifying both the number and size of subgroups as well as the position of individuals within the resulting structures. The latter has an advantage over correlation-based (e.g., Shaw, 2004; Van Knippenberg et al., 2011) and other faultline measures (e.g., Gibson & Vermeulen, 2003; Trezzini, 2008) that neither report subgroup membership nor allow for the identification of influential actors.[8]

[8]To illustrate the differences between the proposed measure for intersecting faultline structures and existing faultline measures, correlations between IFL, ASW (Meyer & Glenz, 2013), $subgroup\ strength$ (Gibson & Vermeulen, 2003), FLS (Shaw, 2004), and PMD_{cat} (Trezzini, 2008) are computed for all organizational units in the subsample, using the *asw.cluster* package (Glenz, 2016). The results are listed in appendices A.2 and A.3. Note that the values should be considered with caution as *asw.cluster* is not featured in the CRAN repository and, more alarming, failed to calculate the measures by Thatcher et al.

This being said, the proposed measure has an alleged flaw which has already been subject to criticism in methodological faultline literature (e.g., Thatcher & Patel, 2012). As briefly mentioned in section 3.2.4, graph theoretical approaches only allow for categorical variables, whereas continuous variables need to be categorized. However, the criticism is not warranted as social identity and self-categorization theories imply that inter-individual distinctions are based on categorizations which require salient differences. Similarly, Shaw (2004) argues that cognitive categorization processes among individuals occur by nature, justifying the categorization of continuous attributes.

5.1 Practical implications

The empirical findings in this paper have several implications for company managers and other practitioners.

Taken together, the results raise awareness for the ambiguous effects of (intersecting) faultline structures on employee absence behavior. More precisely, attribute similarity across demographic structures might reduce absenteeism, whereas structural dissimilarities might foster voluntary absence behavior. Either way, multidimensional team compositions need to be adequately addressed to prevent potentially negative business consequences.

In practical terms, human resources managers are advised to both regularly assess the multidimensional alignments of team attributes and to evaluate, for instance through employee surveys, if faultlines exist only on paper or whether they are actively perceived by team members. If necessary, targeted intervention strategies should be developed to countervail negative impacts at an early stage.

The latter can effectively be achieved in several ways. First, managers are encouraged to promote pro-diversity views (e.g., by adapting their company's image) to highlight the benefits of diverse work teams (McKay & Avery, 2005; Homan, Van Knippenberg, Van Kleef, & De Dreu, 2007a). Second, communication among employees should be enhanced, for instance by convening regular meetings or implementing

(2003), Bezrukova et al. (2009), Lawrence & Zyphur (2011), and Van Knippenberg et al. (2011).

intra-organizational communication systems to prevent subgroup formation. Moreover, if present, crisscrossing employees should be trained to mediate between subgroups. Lastly, along with common organizational goals, an overriding group identity should be created to strengthen team identification and commitment among employees (Rico, Sánchez-Manzanares, Antino, & Lau, 2012).

5.2 Limitations and future research directions

Despite the conceptual and methodological contributions of this paper, the empirical analysis still faces several challenges.

First, while the findings suggest that age × gender intersecting faultline structures might be related to voluntary absence behavior, the causal mechanism linking intersecting faultlines and employee absenteeism is not explicitly tested in this paper. Hence, future studies should aim at complementing objective archival data with subjective data on employees' perceptions to assess the posited causal mechanism, for instance by employing mediation analyses as proposed by MacKinnon, Fairchild, & Fritz (2007) and Hayes (2009) or Imai, Keele, & Tingley (2010), respectively.

In this context, more elaborate statistical models using negative binomial regression should also be tested. The choice for an overdispersed Poisson model for the empirical analyses in this paper was, in the first place, motivated by computational restrictions. In line with Johns (2011) and Bamberger & Biron (2012), negative binomial models might be more appropriate for handling overdispersed absence data. Unfortunately, implementing negative binomial models in JAGS requires a large number of iterations – Jackman (2009, p. 280) mentions several hundred thousand iterations as a reference value – for the Markov chains to converge properly. To encourage future research on this topic, an executable JAGS sample code for negative binomial multiple membership models is provided in the replication data. Moreover, while this study used non-informative priors to mimic maximum likelihood estimation, future studies could exploit the potential of Bayesian methods by specifying subjective priors to include existing knowledge on absence behavior.

A second limitation concerns the cross-sectional research design of the present study which cannot sufficiently control for confounding variables. Subsequent studies should adopt longitudinal designs to enhance causal inferences and, substantively, analyze both temporal patterns in employee absence behavior and the effects of emerging faultline structures over time. The latter is particularly important since Harrison, Price, Gavin, & Florey (2002) show that the effects of demographic diversity on team functioning diminish in the long run, whereas, at the same time, the effects of psychological diversity intensify.

Third, only work teams in one organizational setting are covered in the study which limits the generalizability of the empirical findings. Given that Switzerland has comparatively high levels of GDP, employment rate and overall socioeconomic status (OECD, 2015), the results might not be generalizable to countries with poorer economic conditions. Consequently, future studies should attempt to replicate the empirical findings in settings where both socio- and macroeconomic characteristics differ. This replication strategy might further enable investigating the economic antecedents of individual-level voluntary absence behavior. As suggested by Steers & Rhodes (1978), subsequent analyses could aim at integrating social psychological and economic perspectives on employee absenteeism by extending the existing theoretical framework with macroeconomic predictors, such as regional unemployment rates. Similar reasoning applies to macro-level geographic predictors that potentially constrain an employee's ability to attend work as briefly mentioned in section 3.3. Moreover, studies in the same setting could exploit Switzerland's distinct geographical features to approximate the effects of different cultural norms on absence behavior.

Notwithstanding these methodological limitations, several future advancements in measuring faultlines should be tackled to gain new insights into the complex relationship between diversity and faultline structures. To begin with, since the notion of intersecting faultlines differs conceptually from traditional faultline theory, the empirical analyses in this paper neither take the number nor size of emerging subgroups into account. Still, the required information can easily be obtained by extracting the number and size of components from each intersection graph. As recommended by Thatcher

& Patel (2012), both these overall structural measures as well as individual affiliations and positions within subgroups should be addressed. Closely related is the above discussed notion of crisscrossing actors resulting from overlapping memberships which future studies should focus on as recommended by Meyer and colleagues (2014) and Thatcher & Patel (2012) alike. In sum, more systematic analyses of distinct structural patterns should become the focus of attention in subsequent studies.

Finally, one major benefit of adopting a graph theoretical perspective on faultlines lies in its compatibility with all kinds of social structures, especially since only hypothetical faultlines are analyzed to date. Following the call by Thatcher & Patel (2012), linking these objective dividing lines to cognitive faultlines – for instance by adapting Krackhardt's (1987; cf., Brands, 2013) *cognitive social structures* concept – are fruitful directions for future research.

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APPENDIX

A.1 Means, standard deviations, and Spearman intercorrelations

Table 6. *Means, standard deviations, and intercorrelations (Spearman) of study variables (N = 2293)*

			Correlations									
Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. Absenteeism	1.10	1.93	—									
2. Age	46.36	10.59	−0.15***	—								
3. Gender (0 = male; 1 = female)	0.32	0.46	−0.01	−0.08***	—							
4. Tenure	21.32	13.01	−0.11***	0.64***	−0.36***	—						
5. Absence norms	0.04	0.04	0.04	0.03	0.00	−0.01	—					
6. Age × gender faultlines	0.18	0.11	0.04	0.10***	−0.14***	0.11***	−0.05***	—				
7. Age × language faultlines	0.28	0.13	−0.05*	0.15***	0.04	0.08***	−0.02	0.64***	—			
8. Team size	8.63	2.37	−0.06***	0.04*	0.03	−0.04*	0.22***	−0.08***	0.09	—		
9. Occupation (0 = blue collar; 1 = white collar)	0.36	0.48	0.09***	−0.11***	−0.01	0.02	−0.21***	0.08***	−0.13***	−0.45***	—	
10. Lead (0 = no lead; 1 = lead)	0.10	0.30	−0.04	−0.06***	−0.16***	0.10***	0.02	0.00	0.00	0.01	0.07***	—

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A.2 Comparison between age × gender faultline measures

Table 7. *Means, standard deviations, and intercorrelations (Pearson) of age × gender faultline measures (N = 464)*

			Correlations				
Variables	Mean	SD	1	2	3	4	5
1. IFL	0.17	0.11	—				
2. ASW (Meyer & Glenz, 2013)	0.64	0.12	0.16***	—			
3. $Subgroup\ strength$ (Gibson & Vermeulen, 2003)	0.46	0.15	−0.55***	0.01	—		
4. FLS (Shaw, 2004)	0.13	0.11	0.15***	0.17***	0.38***	—	
5. PMD_{cat} (Trezzini, 2008)	0.23	0.05	0.02	−0.25***	0.26***	0.46***	—

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A.3 Comparison between age × language faultline measures

Table 8. *Means, standard deviations, and intercorrelations (Pearson) of age × language faultline measures (N = 464)*

Variables	Mean	SD	Correlations 1	2	3	4	5
1. IFL	0.27	0.13	—				
2. ASW (Meyer & Glenz, 2013)	0.65	0.13	0.17***	—			
3. $Subgroup\ strength$ (Gibson & Vermeulen, 2003)	0.18	0.11	−0.40***	0.02	—		
4. FLS (Shaw, 2004)	0.05	0.05	0.39***	0.13***	0.31***	—	
5. PMD_{cat} (Trezzini, 2008)	0.20	0.03	−0.31***	−0.07	0.13*	−0.02	—

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.