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Being Different, Being Absent? A Dynamic Perspective on Demographic Dissimilarity and Absenteeism in Blue-Collar Teams

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Being Different, Being Absent?
A Dynamic Perspective on Demographic Dissimilarity and Absenteeism in Blue-Collar Teams

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BEING DIFFERENT, BEING ABSENT? A DYNAMIC PERSPECTIVE ON DEMOGRAPHIC DISSIMILARITY AND ABSENTEEISM IN BLUE-COLLAR TEAMS

ABSTRACT

This study offers a new theoretical and empirical perspective on the dynamic effect of demographic dissimilarity on absenteeism behavior by team members over time. Integrating social identity theory with the theory of anchoring events (i.e., key social interactions), we propose that individual absenteeism behavior depends on the relational dissimilarity to the team age and gender. Using a sample of 2,711 individual newcomers in 820 blue-collar teams tracked over seven years, we show that gender and age dissimilarity effects are not constant over time; rather, dissimilar individuals increase their absences more strongly over the years. Particularly, women and older employees in predominantly male and younger teams show a steeper increase in absenteeism over time and, accordingly, higher absolute absenteeism at later stages of team membership than do their less dissimilar counterparts. We discuss the implications for relational demography and diversity theory as well as for diversity management.

Keywords: diversity; relational demography; absenteeism; growth modeling

Former minority groups (e.g., women and older workers) are increasingly represented in today's workforce. In OECD countries as a group, the workforce participation of women has increased by 9 percent since the year 2000, while the number of workers aged between 55 and 65 years has gone up by 26 percent (Organization for Economic Cooperation and Development, 2018). Accordingly, women and older employees are entering teams formerly staffed exclusively with younger men. This trend is especially salient in production or blue-collar jobs, where the female worker ratio was traditionally low and older workers were largely underrepresented given early retirement caused by physical strain in many blue-collar jobs. In Switzerland, for example, the number of women working in blue-collar jobs has increased by 20 percent since 2000, and the number of blue-collar workers aged between 55 and 65 years by 36 percent (Swiss Federal Statistical Office, 2018).

In face of such developments of increasing representation of demographically non-traditional group members in certain team contexts, it is not surprising that growing scholarly attention has been devoted to the consequences of being demographically dissimilar to others in a work team (e.g., Chattopadhyay, George, & Shulman, 2008) or larger work unit (e.g., Chatman & Spataro, 2005). This research, subsumed under the so-called relational demography approach, argues that an individual's relative level of demographic dissimilarity in a social unit affects outcomes at the individual level (for reviews of the relational demography literature see Guillaume, Brodbeck, & Riketta, 2012; Riordan, 2000).[1] Thus, the relational demography approach complements traditional diversity studies, which consider the effects of the whole unit's diversity on collective outcomes (Chattopadhyay et al., 2008).

From early studies (Tsui, Egan, & O'Reilly, 1992) to most recent publications (David, Avery, Witt, & McKay, 2015), withdrawal behavior has been a core focus in relational demography research. Indeed, understanding the implications of relational demography for absenteeism seems highly relevant as "employee absence takes a heavy toll on worker productivity" (Biron & Bamberger, 2012: 901). Absenteeism disturbs work processes, delays schedules, increases the workload for coworkers, and may require hiring costly temporary workers to replace absent employees (Mason & Griffin, 2003; Ybema, Smulders, & Bongers, 2010). The costs can total up to 15% of a company's payroll (Navarro & Bass, 2006).

Most existing research on relational demography and withdrawal behavior has drawn on social identity (Tajfel & Turner, 1986) and self-categorization theories (Turner, 1987) to predict more absenteeism for individuals who differ demographically from other group members (e.g., Tsui et al., 1992). Yet the empirical findings are rather inconclusive, with generally small effects sizes (Guillaume et al., 2012) ranging from nonsignificant (e.g., David et al., 2015) to positive

[1] It should be noted that the term *relational demography* has been used to refer not only to individual-within-team/unit dissimilarity but also to dyadic leader-follower dissimilarity (e.g., Dwertmann & Boehm, 2016). While we acknowledge the importance of demographic differences in leader-follower dyads for individual-level outcomes, the dyadic focus does not cross the individual-group boundary, so Riordan (2000) has recommended treating dyadic dissimilarity as a distinct level of theory and research. Due to this difference and our interest in the effect of dissimilarity in work teams we have chosen to focus only on the individual within-team/unit perspective.

(e.g., Tsui et al., 1992). While diversity researchers who focus on the team level and/or use performance as a criterion (Srikanth, Harvey, & Peterson, 2016; van Dijk, Meyer, van Engen, & Loyd, 2017) have started to recognize temporal dynamics as an explanation for these inconclusive effects, little is known about how demographic differences play out over time on the *individual level* and how this affects individual withdrawal behavior. Existing individual-level studies, while they noted the existence of time-variant effects of demographic dissimilarity, lacked a clear theoretical argument about the temporal patterning and/or did not apply longitudinal data and methods to test rigorously for dynamic effects (e.g., Chatman & Flynn, 2001; Hobman & Bordia, 2006; Sacco & Schmitt, 2005). Hence, it remains largely unclear how the effect of individual-level demographic dissimilarity in teams unfolds over time, what effect this has on individual absenteeism, and what factors shape the unfolding process.

To address these shortcomings of a limited theoretical focus and insufficient research designs we take a temporal perspective on dissimilarity effects. We integrate the social identity approach—a synthesis of social identity and self-categorization theory (Haslam, 2011)—with the literature on anchoring events: events, or short sequences of focal social-exchange events, that color participants' perceptions of all future exchanges in the relationship (Ballinger & Rockmann, 2010). We argue that perceived initial discrimination against out-group individuals is stored in the individual's autobiographical memory (Conway & Pleydell-Pearce, 2000). Because such anchoring events are easily retrieved, they may negatively taint all subsequent evaluations of social interactions with the majority in the team, so that perceptions of social isolation and alienation can accumulate over time and ultimately increase absenteeism behavior.

As a further theoretical refinement, we propose that the dynamic consequences of demographic dissimilarity are asymmetric for different demographic groups. In particular, members of traditionally subordinate groups (i.e., women and older employees) often have a token status (Kanter, 1977) that involves higher performance standards and scrutiny than are applied to majority group members (male and younger employees). This is particularly the case if they enter a context with strong job prototypes (Perry, 1994) for male and younger workers, such as a blue-collar setting (Glick, Wilk, & Perreault, 1995; Kulik, Perera, & Cregan, 2016). In consequence, they are more likely to encounter and to perceive discriminatory treatments that they interpret as anchoring events, and that may generate disproportionately increasing absenteeism trajectories for them .

In summary, we attempt to make three significant theoretical and empirical contributions. First, we integrate the social identity approach (Haslam, 2011) with anchoring events theory (Ballinger & Rockmann, 2010) to provide a theoretical framework for understanding the immediate and long-term effects of demographic dissimilarity on individual withdrawal behavior. Even though "social identity is dynamic" (Hogg & Terry, 2000: 124) and the effects of relational dissimilarity have been conceptualized to vary over time as dissimilar individuals use different social enhancement strategies (Chattopadhyay, Tluchowska, & George, 2004), there have been very limited attempts to integrate this concept into theory development and empirical studies (for exceptions, see Harrison, Price, Gavin, & Florey, 2002; Zhu, Tatachari, & Chattopadhyay, 2017). Therefore, a core aim of this study is to add a temporal perspective to social identity processes of demographical dissimilar individuals in teams through the time-based lens of anchoring events by proposing and testing that social identity processes for dissimilar team newcomers do not have an immediate effect on absenteeism, but rather trigger negative anchoring events that affect absenteeism behavior only later. Thus we address a central criticism of theory formulation not only in diversity and relational demography research (Li, Meyer, Shemla, & Wegge, 2018), but in management and organizational behavior research in general: that most theory does not consider when, and for how long, an effect is likely to occur (Cronin, Weingart, & Todorova, 2011).

Second, we refine this theoretical contribution to the social identity literature by hypothesizing and testing an asymmetric effect of demographic dissimilarity (Chattopadhyay, 1999). The literature on asymmetric effects has produced mixed results, for example with regard to gender. Tsui and colleagues (1992) found higher withdrawal behavior among dissimilar men but not among dissimilar women, while other studies reported more perceived discrimination for dissimilar women than for men (Avery, McKay, & Wilson, 2008), and still other studies found no effect of gender at all (Chattopadhyay, 1999). We clarify these inconsistencies by arguing that asymmetric relational effects surface only in the long run. Incorporating the concepts of status characteristics (Berger, Hamit, Robert, & Morris, 1977) and token status (Kanter, 1977), we propose that low-status groups (women and older employees) are particular likely to perceive strong negative anchoring events that should lead to steeper absenteeism trajectories over time. The existing literature on asymmetric relational demography (e.g., Avery et al., 2008; Chattopadhyay, 1999) could not assess this possibility, as it theorized only stable asymmetric effects and studied them in samples with a mixture of long-tenured team members and newcomers.

Third, as an empirical contribution, we employ an extensive repeated-measure design on relational demography and on absenteeism and draw on recent methodological advancements in modeling count data (like absenteeism) in a growth model framework (Aiken, Mistler, Coxe, & West, 2015). Management and organizational behavior researchers have been generally slow in adopting appropriate modeling strategies for count-based dependent variables (Blevins, Tsang, &

Spain, 2015), especially in complex longitudinal or multilevel designs. This might have hampered knowledge generation. In this regard, we demonstrate a methodological way forward that might inspire diversity and other organizational research areas.

THEORY AND HYPOTHESES

Our relational demography conceptualization can be described as a frog-pond or an individual-within-the-group concept (Klein, Dansereau, & Hall, 1994), in which a person's standing in relation to other members in a team is linked to that person's individual outcomes. To conceptualize relational demography in our study, we focus on so-called surface-level demographic attributes such as gender and age (Harrison, Price, & Bell, 1998), which are easily accessible, culturally meaningful, and immutable and thus are highly relevant to social identity processes (Fiske, 1998). Compared to deep-level diversity attributes (e.g., personality, values), surface-level facets are immediately recognizable (Harrison et al., 2002) and should thus be particularly salient when newcomers enter a team..

Demographic Dissimilarity and Absenteeism

Most studies have used self-categorization theory (Turner, 1987) and social identity theory (Tajfel & Turner, 1986)—commonly summarized as the social identity approach (Haslam, 2011)—to predict higher individual absenteeism due to dissimilarity in employees' social environment. This approach suggests that people use demographic characteristics, e.g., gender and age, to classify themselves and others into different social categories (Tsui et al., 1992), leading to in-group versus out-group distinctions. Viewing one's own in-group more favorably helps to maintain a positive identity (Tajfel & Turner, 1986). This is in line with research on intergroup relations, which demonstrates that subgroup distinctions can go along with intergroup bias, where trust and the willingness to cooperate with out-group members suffer and the likelihood to feel the effect of out-group bias and conflict increases (Chattopadhyay et al., 2008; Hewstone, Rubin, & Willis, 2002). Accordingly, for more dissimilar individuals from the team their distinct, minority identity should lead to identity threat and feelings of discrimination, social exclusion and alienation (Avery et al., 2008; Jansen, Otten, & van der Zee, 2017). The relational demography model by Riordan, Schaffer, and Stewart (2005) also stresses that minority members' recognition of their own demographic difference from the majority increases their likelihood of perceiving discrimination, unfair treatment, and social exclusion. Empirically supporting these assumptions, Avery and colleagues (2008) found that perceived discrimination was significantly more prevalent among employees, particularly women, with fewer same-sex coworkers. Such perceptions of discrimination and other forms of hostility of dissimilar team members might, in turn, increase their absenteeism behavior as an “escape from, compensation for, or even protest against aversive or demoralizing work circumstances” (Bakker, Demerouti, Boer, & Schaufeli, 2003: 342).

However, only a few studies have found such a positive effect of demographic dissimilarity on absenteeism (e.g., Tsui et al., 1992), while other studies report null effects (e.g., David et al., 2015). In response to the inconsistent findings, researchers have called for a more complex take on dissimilarity by including characteristics beyond the commonly researched surface-level attributes or by considering the intersectional effects of multiple demographic dimensions (Hall, Hall, Galinsky, & Phillips, in press; Riordan et al., 2005). While we acknowledge the importance of a broader conceptualization of the dissimilarity construct itself, it might also be useful to adopt a more dynamic perspective. Initial empirical evidence suggests that the effects of demographic dissimilarity on turnover vary over time (Sacco & Schmitt, 2005) and that coworker perceptions affect the development of individual absenteeism trajectories (Dello Russo, Miraglia, Borgogni, & Johns, 2013). But those studies tell us little about the theoretical underpinnings and how the findings might extend to the relationship between demographic dissimilarity and absenteeism.

The Time-Varying Effect of Demographic Dissimilarity

Given the social contact hypothesis (Allport, 1954) and the prediction that positive contact is more common than negative contact (Graf, Paolini, & Rubin, 2014), relational demography researchers have occasionally speculated that continuous social contact across demographic differences on the team decreases prejudice and discrimination (e.g., David et al., 2015; Riordan et al., 2005), and thus absenteeism of dissimilar individuals might decrease over time. A key assumption of this past research was that team members closely observe interactions with a dissimilar other and use them to form a more accurate individuating impression, which then allows them to recategorize the "different" person. We challenge this assumption, as a history of negatively perceived interactions with dissimilar individuals undermines accurate judgments and assessments of subsequent interactions and might negatively bias evaluations (Ballinger & Rockmann, 2010). By questioning the assumption of the social contact hypothesis, we align well with other studies in the relational demography field. Tsui and Gutek (1999: 167), for instance concluded, "Social psychological research has shown convincingly that contact alone is not sufficient and that it can in fact enhance or deepen inter-group hostility".

We argue that anchoring events theory (Ballinger & Rockmann, 2010) provides a better rationale than social contact theory (Allport, 1954) to theorize about dynamic effects of dissimilarity on absenteeism. We suggest that demographic dissimilarity of team members increases the likelihood of negative anchoring events that may set them on a path of more strongly increasing absenteeism. This prediction is most likely to be true in stereotyped contexts such as blue-collar settings, where strong job stereotypes lead to significant negative perceptions of social contacts with demographically dissimilar others who do not match the job stereotype.

Moreover, in such low-skilled blue-collar contexts sophisticated recruitment processes for internal and external hires are not widespread, and individuals are recruited mainly out of need for further human capital, without considering the (demographic) fit to the team (Brown, Dickens, Gregg Paul, Machin, & Manning, 2001; Keller, 2017). This creates an environment where individuals, especially non-traditional team members, face difficulties in adjusting to their team and are more likely to experience negative contact. As we note above, anchoring events—whether one key exchange or a sequence of key exchanges in social relationships between a focal individual and a target (e.g., individual, group, or organization)—are encoded in autobiographical memory (Conway & Pleydell-Pearce, 2000) and are subsequently used to judge and evaluate all further interactions with the target (Ballinger & Rockmann, 2010). [2]

A set of factors determines the likelihood that events will function as anchors. Most important for our application are the following factors discussed by Ballinger and Rockmann (2010). First, strong anchors emerge from events with a negative balance (i.e., the dependent individual demands more resources or information than he/she receives). Generally, negative instances are better stored in long-term memory than ones with a neutral or positive balance (Kensinger & Corkin, 2003), because negative events cause greater affective arousal and therefore are easier to retrieve in later interactions with the target (Labianca & Brass, 2006). Second, events stand out when the treatment of oneself differs meaningfully from the treatment of referent individuals, such as people in the same team (Roberson, 2006). While any event involving negative balance or atypical treatment can set an anchor, events that happen relatively early in a new social relationship have been theorized to set the strongest anchor, because the

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[2] Note that theoretically an anchoring event can emerge from a single significant exchange. However, more recently researchers have noted that in reality a sustainable shift in an exchange relationship from balanced to negative is likely to result from a sequence of events (Solinger, van Olffen, Roe, & Hofmans, 2013). We would expect this to be true in the case of demographic dissimilarity.

uncertainty and dependency of individuals new to a social context (Saks & Ashforth, 1997; Wang, Zhan, McCune, & Truxillo, 2011) create optimal conditions for consequential, unexpected events (Gundry & Rousseau, 1994; Louis, 1980). Once anchor events occur, they bias interpretations of any subsequent interaction, even if the new interaction brings the focal individual "objectively" positive returns.

These theoretical ideas seem to fit well to explain the temporal dynamics of absenteeism by demographically dissimilar individuals entering a workgroup. First, dissimilar individuals are categorized in an out-group position and therefore are very likely to perceive negative experiences in exchange relationships with their team peers, such as low social integration or even discriminatory treatment (Avery et al., 2008; Guillaume et al., 2012). Second, high proximity within the team lets individuals compare the treatment they receive from colleagues with what they have seen other team members receive (Shah, 1998). Because the majority members are similar to each other (i.e., they share a common subgroup), they are in fact likely to cooperate more and trust each other more compared to their interaction with the dissimilar out-group member (Hewstone et al., 2002). Accordingly, the dissimilar individual may perceive his or her own treatment as a significant negative deviation from the team norm. While the feeling of exclusion and discrimination is troublesome for all dissimilar team members, it may be particularly troublesome for dissimilar newcomers. They depend heavily on reciprocity, given their own inexperience in the specific team context and their relative lack of task-specific competences (Saks & Ashforth, 1997; Wang et al., 2011), so they are vulnerable to disappointing exchanges.

Thus, even if the social exchange relationships normalize over time and the individuals are "objectively" less isolated and discriminated against, they may still negatively interpret the new situations by recalling the initial anchoring events. Each subsequent interaction with the dissimilar majority on the team may lead to a recall of the initial anchoring event, which thus becomes more deeply rooted in the focal individual's memory view of the long-term self (Ballinger & Rockmann, 2010). Furthermore, it is also likely that individuals will selectively search for new negative events that confirm their initial negative judgment, as extant research on confirmation bias in human decision-making reliably demonstrates (for a review, see Nickerson, 1998).

Based on this reasoning we argue that perceived social-exclusion of dissimilar individuals does not materialize directly after team entry in terms of absenteeism behaviors, but might rather affect absenteeism behaviors later in time, when dissimilar individuals perceive an accumulation of negative social experiences through the prism of the initial negative anchoring event. In the short run, individuals may be able to stand perceptions of being socially excluded by drawing on other resources (e.g., from outside work; David et al., 2015). A probation period may also make them avoid acting immediately on their negative emotions through absenteeism behavior, so as not to risk their new position. However, over time they may perceive their situation as increasingly frustrating. Also research on social ostracisms (Williams, 2007) backs this argumentation by proposing that for a certain amount of time socially excluded individuals can apply strategies to satisfy their need for belonging, such as prosocial behavior to help them become part of the in-group. If, however, individuals experience multiple episodes of hostile ostracism—such as perceptions of constant biased treatment based on an initial negative anchoring event—their ability to use resources to compensate their need for belonging diminishes (Williams, 2007). Accordingly, we expect an increase in absenteeism levels for individuals who are demographically dissimilar (in surface-level categories, such as age and gender), particularly as time goes on. Thus, we propose the following hypothesis:

Hypothesis 1a. An individual's gender dissimilarity predicts individual absenteeism trajectories, when an individual's gender is more dissimilar from the team's gender, the individual's absenteeism increases more steeply over time.

Hypothesis 1b. An individual's age dissimilarity predicts individual absenteeism trajectories, when an individual's age is more dissimilar from the team's age, the individual's absenteeism increases more steeply over time.

Asymmetric Effects for Gender and Age

Thus far, we have predicted identical effects whether the "different" person is a female (older) worker entering a predominantly male (younger) group, or vice versa. But there are good reasons to expect asymmetrical effects, as members of some demographic groups are generally more likely to perceive negative anchoring events in terms of social interactions with the majority.

This idea of asymmetric effects of demographic dissimilarity is not completely new (see, e.g., Chattopadhyay, 1999). However, the asymmetric effects reported in the literature have been inconsistent. For instance, with regard to gender dissimilarity, Avery et al. (2008) found dissimilarity to have a greater effect on perceived discrimination among women than men. In contrast, Tsui et al. (1992) found higher withdrawal behavior among dissimilar men but not among dissimilar women. Moreover, a third group of studies has found no evidence of any asymmetric effects for gender (e.g., Chattopadhyay, 1999). Again, we suggest that these inconsistent findings can be partly explained by a missing temporal perspective, as the effect of asymmetries might surface, particularly later in time after team entry. As previously outlined, we expect that dissimilar individuals entering a team have a high likelihood to perceive negative anchoring social events during their team membership, such as being singled out for discriminatory treatments that negatively bias their evaluation of subsequent team interactions, and in consequence lead to higher absenteeism later in time.

We assume that the probability of perceiving strong negative anchoring events is particularly high for members of traditionally subordinate or low-status groups—such as female and older employees—compared to members of superior or high-status groups—such as male and younger employees. The concepts of status expectations (Berger et al., 1977) and tokenism (Kanter, 1977) propose that dissimilar low-status groups, such as female and older employees, are especially visible and are often targets of evaluation biases and discriminatory treatment (Roth, 2004). The empirical literature supports this assumption by reporting negative evaluation of women in male-dominated settings (e.g., Ellemers, 2018; Leslie, Cimpian, Meyer, & Freeland, 2015; Turco, 2010) and instances where women were made to work twice as hard as their male colleagues to prove their competence (Kanter, 1993). Furthermore women have been found to perceived more workplace mistreatment such as discrimination (McCord, Joseph, Dhanani, & Beus, 2018), while males entering female-dominated contexts do not receive biased evaluations and performance pressure (e.g., Hekman, Johnson, Foo, & Yang, 2017; Williams, 1992).

Biased stereotypes also exist for older workers, such as ascription of generally lower performance (Gordon & Arvey, 2004), more resistance to change (Weiss & Maurer, 2004), and less potential for development (Maurer, Barbeite, Weiss, & Lippstreu, 2008). Furthermore, recent empirical research has shown that older workers in relatively young work groups experience age “stereotype threats”, in which negative age stereotypes affect their own self-perceptions (Kulik et al., 2016). In consequence it is also plausible to assume that older employees have a token status and are prone to perceive potential biases and discrimination when entering a dissimilar team compared to younger employees.

Both effects, for female and older employees, are likely salient in blue-collar settings, where the implicit job prototype (Perry, 1994) or job stereotype (Finkelstein, Burke, & Raju,

1995) assumes that young and male employees best fit physically demanding jobs. In support of this argument, Perry and associates (Perry, 1994; Perry, Kulik, & Bourhis, 1996) posit and find in a series of studies that individuals store information about jobs and job incumbents in person-in-job prototypes and that applicants who match the job prototype are evaluated more favorably. Specifically for our study context, Kulik et al. (2016) find that older workers doing manual labor are particularly susceptible to age stereotype threats, and other studies reveal that both employers and employees are convinced that the performance decline due to age is more pronounced in manual occupations than in other less physical jobs (e.g., Loretto & White, 2006).

Accordingly, dissimilar female or older individuals are more likely to perceive strong negative anchoring events than male and younger individuals. Moreover, employees who are constantly confronted with discrimination grow to expect it and are thus more likely to detect even subtle discrimination in further social interactions (McCord et al., 2018). We therefore assume that the self-reinforcing mechanism in which initial anchoring events shape subsequent perceptions is particularly reasonable for female and older employees, and this should manifest in a steep increase of absenteeism over time. Hence, we propose that

Hypothesis 2a. An individual's gender dissimilarity has a greater effect on the absenteeism trajectory among women than men, so that dissimilar female individuals exhibit a steeper absenteeism trajectory than dissimilar male individuals.

Hypothesis 2b. An individual's age dissimilarity has a greater effect on the absenteeism trajectory among older individuals than younger individuals, so that dissimilar older individuals exhibit a steeper absenteeism trajectory than dissimilar younger individuals.

METHODS

Sample and Procedure

We obtained data on all blue-collar workers of a large business unit of a Swiss public service company at seven time-points between 2010 and 2016 from the official archival HR records. The business unit had approximately 13,120 employees in 1,454 teams, working mostly on sorting and delivery tasks. All teams held regular team meetings, had one common supervisor, and held members mutually accountable for outcomes (i.e., if a team member was absent, another team member would step in). To assure that the studied individuals are comparable in their development of absenteeism, we sampled only employees who were new to a team at the start of the data collection. We collected their demographic attributes, absenteeism data, team affiliation, and demographics of team colleagues for their first year of membership and for each of the six following years. In line with previous research, we chose a one-year interval for aggregation of absenteeism data, for both theoretical and methodological reasons (e.g., Bacharach, Bamberger, & Biron, 2010). Theoretically, the one-year period is a salient metric for members in the organization under study, as it matches the company's absence accounting period, which employees are likely to consider in regulating their absences (Harrison & Martocchio, 1998). Methodologically, a year is long enough to yield a meaningful number of absence days given the low absence base-rate for most employees (Nguyen, Groth, & Johnson, 2013).

The sample at Time 1 consisted of 2,738 newcomers from 820 blue-collar teams with 10,304 members. To assure that single instances of excessive absenteeism do not bias our results (Hammer & Landau, 1981), we excluded observations with absenteeism values above the 99th percentile from all analyses.[3] This resulted in a final sample of 2,711 newcomers, 10.33 % of whom were new hires who were new to both the organization and the team, while the rest were internal transfers, who were new only to the team, not to the organization. Most of the newcomers were male (54.11%), and their average age was 43.58 years (SD = 11.03). The teams had on average 14.85 members (SD = 5.91) with a mean age of 45.97 years (SD = 4.10) and a

[3]We obtained similar results for all relationships both from further restricting the sample to observations below the 95th percentile and from using the unrestricted sample.

share of 41.52% women.

Team membership was not stable over time; 1,203 (44.35%) of the newcomers changed teams at least once. Since the relevant information (i.e., absenteeism and their demographic dissimilarity in the new team) could still be obtained after team change, we included the post-change data in our analyses. We think that demographic dissimilarity plays an important role for team changers also. We know from our communication with the company that internal hiring and transfer procedures are rather informal and are designed merely to fill requirements, not to create a (demographic) fit between the newcomer and the team. Hence, it is unlikely that team changers and the new team will have more positive expectations towards each other. Furthermore, our theoretical reasoning predicts that dissimilar individuals who have experienced a negative anchoring event are primed to expect further negative treatment. Specifically, we theorized that every additional interaction with a dissimilar majority will revive the memory of the anchoring event, which thus becomes incorporated into the individual's view of his/her long-term self. We would therefore expect the demographic dissimilarity effect on absenteeism to carry over to the new team, and thus we retain team changers in our sample.[4]

Still, 877 (32.35%) workers left the business unit or the organization altogether and hence had missing values after exit. As the literature recommends, we included these individuals in the analysis, as they provide valuable information until drop-out (Hox, 2010).[5]

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[4] While we report results considering all observations from team changers, in a robustness check we inspected whether results remained the same in a restricted sample where we set observations to missing after team change; our results did not change. Furthermore, team change did not affect our effects in a four-way interaction (Gender[Age] × Share of Women[Average Age] × Time × Team Change). This indicates that an individual's negative experience of being demographically dissimilar carries over to a new team. This finding also empirically supports our rationale for retaining team changers in our sample. Results of the robustness checks are available from the first author.

[5] Tests of attrition showed that individuals who left the business unit were older (M = 42.715 vs. 45.085, t = -5.277, $p < .001$) and showed higher absenteeism (M = 4.848 vs. 14.551, t = -10.181, $p < .001$) than those who remained, but were comparable with respect to gender, tenure, team size, share of women on a team, and average age in the team. The higher age and absenteeism for drop-outs bias our hypotheses tests only when dropping out is also linked

Measures

Absenteeism. We obtained absence data from official HR records to avoid biased self-reporting. Following previous studies of absenteeism (e.g., Bacharach et al., 2010), we measured absence as the number of workdays lost in the last year for any reason other than approved vacation, military service, training, maternity leave, or a personal day. We measured absence as the total number of days lost rather than as frequency regardless of duration, because days lost better capture the economic costs arising from absence (Nguyen et al., 2013).

As a count variable, the absence measure was highly skewed to the right (Time 1: skewness = 4.475, $p < .001$; kurtosis = 26.072, $p < .001$), and non-normality was indicated by significant Shapiro–Wilk (Time 1: W = .547, V = 707.701; $p < .001$) and Kolomogorov–Smirnov tests (Time 1: K-S = .354, $p < .001$). This required special statistical treatment and is discussed in more detail in the "Analyses" section.

Demographic dissimilarity. We focused on gender and age. To measure demographic (dis)similarity at the individual level, researchers have relied mainly on Euclidean distance scores (D-scores) (Joshi, Liao, & Roh, 2011), which have attracted considerable conceptual and methodological criticism over the past years (e.g., Edwards, 1994). Most notably for our application, the D-score masks directional differences and nonsymmetrical effects. This is crucial when we want to test the postulated asymmetries in the dissimilarity effect, and we agree with Riordan and Wayne (2008: 587) that the D-score's "methodological limitations make it inappropriate for further use within relational demography research."

Consequently, to capture dissimilarity effects we used interaction terms between the individual demographic attribute and the demographic composition of the team for the same

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to relational demography (Groves, 2004). A survival model with dropping out as criterion and relational demography as predictor did not reveal an association for any year of the study, giving us confidence in performing longitudinal analyses despite sample attrition.

attribute. More precisely, we followed Sacco and Schmitt (2005) and measured gender similarity as the interaction between an individual's gender and the share of women in a team, and age similarity as the interaction between an individual's age and the average age in the team. Reversing the signs of the similarity effects we obtain the effect of dissimilarity.

Controls. We included five control variables because theoretical and empirical arguments suggest relationships with our focal variables. First, as respondents were from two different departments in the business unit with systematically different work tasks and demands (and hence potentially different risks of being absent), we controlled for all unobserved factors due to *department membership*. We captured the unobserved heterogeneity by including one dummy variable, which exhaustively captured membership in one of the two departments in a given year. Second, as some newcomers had *leadership responsibility* in their team, and leaders might systematically differ from non-leaders in their absence behaviors owing to responsibilities and a set of leader-specific personality traits (Judge, Piccolo, & Kosalka, 2009), we controlled for leadership position with one dichotomous variable. Third, as a substantial number of individuals changed teams between years, we controlled for *team change* by adding a dummy variable, indicating whether an individual moved between teams from one year to another. Obviously, in the first wave, all individuals were assigned a value of zero on this variable. Fourth, as meta-analytic evidence shows an association between tenure and absenteeism (Farrell & Stamm, 1988), and most of our newcomers were new only to the team and not to the organization, we controlled for previous organizational membership by including individual *organizational tenure*. Fifth, we controlled for *team size* in each year, because team size has been shown to affect absenteeism (Markham, Dansereau, & Alutto, 1982).

Analyses

The nature of the data, which involves (a) a count criterion and (b) repeated measures of the same constructs over time, presents major challenges for the data analysis, which we deal with by employing growth modeling in a generalized linear mixed model (GLMM) framework (Atkins, Baldwin, Zheng, Gallop, & Neighbors, 2013).

A count variable typically violates the normal distribution assumption underlying many standard statistical procedures (Long & Freese, 2014). Ignoring the special properties of count variables, or simply transforming the variables through logarithmic transformation, leads to poorly fitting models and to incorrect standard errors and *p*-values (Long & Freese, 2014). Generalized linear models (GLM) from the negative binomial model family can model count data accurately.[6] However, the negative binomial GLM assumes that observations are mutually independent, an assumption likely to be violated in the repeated measures design. Repeated measurements from the same individual may be correlated, and interdependence may be stronger between responses temporally closer to each other (Bliese & Ployhart, 2002). Thus, we drew on the class of generalized linear mixed models (GLMMs, also called "multilevel generalized linear models") and extended the negative binomial GLM to a negative binomial GLMM (for a recent, nontechnical introduction, see Aiken et al., 2015).

The GLMM was built up in steps, increasing complexity by adding random effects and predictors (cf. Bliese & Ployhart, 2002). We adopted the procedure of Singer and Willett (2003) and inserted time-varying variables as level-1 predictors of yearly individual absenteeism and time-invariant predictors on level 2 of the model. To contrast the fit of the models, we followed two procedures (Singer & Willett, 2003): We compared the -2log likelihood values (i.e.,

[6] A range of GLMs for count outcomes is available. The most basic Poisson count model assumes equidispersion (i.e., the mean of the outcome variable equals its variance). In our case, descriptive analyses indicated that the variance of absenteeism far exceeded its mean (M_{T1} = 6.55; Var_{T1} = 305.90). The overdispersed Poisson and the negative binomial model relax the assumption of equidispersion, but we found the negative binomial model to fit significantly better to the data than the overdispersed Poisson. Accordingly, we test our hypotheses using a negative binomial model.

deviances) of the models by a likelihood-ratio test, and we used the Akaike information criterion (AIC), with smaller AIC values indicating a better relative model fit. To make the coefficients more interpretable, we grand-mean centered all continuous independent variables except time (Singer & Willett, 2003). Hypotheses were tested in Stata 15 SE.

RESULTS

Table 1 presents descriptive statistics and the between-person correlations among the study variables.[7] Next, we describe the results of the baseline analyses before moving to the results of the hypothesis testing.

------- *Insert Table 1 about here* -------

Baseline Analyses

First, we assessed whether repeated measurements of absenteeism within individuals are independent. This is normally done by calculating the intraclass correlation coefficient (ICC), but the ICC is not defined for negative binomial GLMMs (Rabe-Hesketh & Skrondal, 2008). Instead, we compared -2log likelihoods from a fixed-intercept-only model and a random-intercept-only model that accounts for nesting of repeated-absence measures in individuals (Aiken et al., 2015). Including the random intercept reduced the -2log likelihood values by 2.25% ($p < .001$), indicating that methods accounting for the interdependence of repeated measures are indeed required.

In the next step, we specified a baseline growth model to establish the absenteeism trajectory and to test for meaningful between-person variation in trajectories, which the

[7] The correlations between the absenteeism variables (Absenteeism, time 0–Absenteeism, time 6) and all other variables reported in Table 1 are weak and mostly not significant. In part this can be attributed to the highly skewed and discrete nature of our absence variable, which carries less information per observation than do continuous data (Raudenbush, 2008). Moreover, the extremely skewed distribution might bias Pearson correlations downward and can lead to underpowered significance tests (Bishara & Hittner, 2012). Applying a general purpose rank-based inverse normal transformation to the absenteeism variable before calculating Pearson correlations to approach normality (as recommended by Bishara & Hittner, 2012) leads to notably higher correlations. Results are available from the first author.

hypotheses explain through a person's demographic dissimilarity. We determined the absenteeism trajectory by entering time as a predictor of absenteeism in the model. The time variable was centered on the first wave (i.e., 0, 1, 2, [...], 6) to assure a meaningful zero point, which allows the intercept to be interpreted as absenteeism in the first year after group entry, conditional on the random effect. For both theoretical and methodological reasons, we decided to model a parsimonious absenteeism trajectory involving only a linear term for time (instead of quadratic and cubic time terms that would allow for more complex trajectories). There is not enough theory to suggest a specific functional form of the individual absenteeism trend, which is why Ployhart and Ward (2011) recommend using parsimonious models to avoid over-fitting and limited generalizability. Methodologically, GLMMs are computationally difficult to fit, especially when they involve many random effects (as would be the case in modeling complex individual functions for time). Even when we used different optimization techniques and different starting values, the model did not converge when it included both a linear and a squared term for time.[8]

When the baseline growth model is specified with a fixed effect for the linear time predictor, absenteeism follows a positive mean trajectory across individuals, as is indicated by a significant coefficient for time ($B = .120$, $p < .001$). To allow the growth trajectory of absenteeism to vary across persons, in the next step we set the effect for time to random. The model with a random effect for time fitted the data significantly better than the model with a fixed time effect (Δ-2log likelihood = 95.22, $p < .001$; ΔAIC = 91.23), indicating meaningful

[8] In a workaround we checked empirically whether a linear time trend conformed with the data. We log-transformed the absenteeism variable to approach a normal distribution and considered it as an outcome in a standard multilevel model, which is less computationally difficult to fit. In this case, only the linear and not the squared time predictor turned out to be significant, lending empirical support for a parsimonious linear time-effect specification.

variation in trajectories between individuals.[9] Thus, in all following models we retained a random slope for time. The significant intercept ($B = 1.033$, $p < .001$) in the baseline growth model indicates that absence is unlikely to be zero at the start of the observation period. The rate ratio (*RR*; Long & Freese, 2014) indicates that each newcomer is absent 2.808 days in his or her first year on the team. One critical feature of the negative binomial GLMM is that the estimates and their interpretation are conditional on specific values of the random-effects distribution (sometimes called unit-specific estimates) and do not provide population-average predictions (Aiken et al., 2015; Raudenbush & Bryk, 2002). Hence, model-based predictions of absence derived from the conditional estimates are not directly comparable to the descriptive absence means in the sample (Atkins et al., 2013) but are in our case lower than the sample means.[10] Moreover, the baseline GLMM model indicates a significant positive effect of time ($B = .122$, $p < .001$; $RR = 1.129$); the *RR* indicates that expected days of absence increase by a factor of 1.129 with every additional year in the group, depending on random effects. The predicted conditional, unit-specific growth trajectory for newcomers is displayed in Figure 1, along with the predicted conditional growth trajectory for all blue-collar employees in the organization as a reference line.[11]

------- *Insert Figure 1 about here* -------

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[9] We also tested the random slope model for autoregressive structure, but it did not fit the data significantly better than a model with an unstructured error covariance matrix. Therefore, we used unstructured error covariance matrices for all models.

[10] Population-average predictions, which can be compared to the sample mean, can be derived from general estimation equations (GEEs; Skrondal & Rabe-Hesketh, 2008). Like the GLMM, the GEE is quite flexible and can deal with longitudinal count data, but it has a number of drawbacks in our context (i.e., it does not provide estimates of variability of the absenteeism slope across individuals, makes stronger assumptions about missing data, and assumes uncorrelated time-varying covariates; Atkins, Baldwin, Zheng, Gallop, & Neighbors, 2013; Raudenbush, 2008). Still, we retested all our hypotheses using GEE and found support for our results from the GLMMs, but with higher absolute absenteeism values closer to the mean values in the descriptive sample. Results are available from the first author upon request.

[11] The trajectory is slightly curved despite the linear time specification. This is caused by the log link function in the count model, which makes it a multiplicative model (Atkins et al., 2013).

Hypothesis Tests

Hypotheses 1 and 2 predict that individual absenteeism trajectories are shaped by a person's gender dissimilarity (Hypothesis 1a) and age dissimilarity (Hypothesis 1b), and that dissimilarity leads to higher absenteeism later in time, particularly for women (Hypothesis 2a) and older workers (Hypothesis 2b). All results are displayed in Table 2. In a three-step approach, we first entered the control variables together with the time predictor (Model 1). Second, we entered individual gender and age as well as the group share of women and average age as time-variant predictors (Model 2). The coefficients of gender and age provide insights into the direct effects of gender and age on absenteeism. We find that women have generally higher absenteeism than men (B = .177, $p < .05$; RR = 1.193), while we do not find significant absenteeism differences due to direct age effects (B = .005, p =.26; RR = 1.005). By testing whether our dissimilarity effects explain variance in absenteeism over and above the variance explained by direct gender (age) effects, we rule out direct gender (age) effects on absenteeism potentially caused by childcare responsibilities or aging-related health issues as alternative explanations for our dissimilarity effects. In a third step (Models 3 & 4), we entered the interactions between individual demographic characteristics and group demographic composition and extended them to three-way interactions with time. The three-way interaction allows us to test whether the effect of demographic dissimilarity varies over time, which lies at the heart of our hypotheses.

Below, we first discuss the results for gender dissimilarity postulated in Hypotheses 1a and 2a, before moving to age dissimilarity, covered by Hypotheses 1b and 2b. As can be seen in Table 2 (Model 3), the interaction female × share of women × time turned out to be significant (B = -.002, $p < .05$; RR = .998), indicating that the effect of gender dissimilarity varies over time. To further inspect the finding, we centered the time variable at each of the seven points, so we could compare the association between gender dissimilarity with absenteeism at different time points. As the interaction measures similarity, negative *B* coefficients indicate that gender similarity decreases the risk of being absent—that is, that gender dissimilarity increases it. We found that gender dissimilarity significantly predicted higher absenteeism only after Time 2, with the following conditional estimates for the interaction female × share of women: Time 0, $B = .001$ ($p = .885$); Time 1, $B = -.001$ ($p = .653$); Time 2, $B = -.004$ ($p = .224$); Time 3, $B = -.006$ ($p < .05$); Time 4, $B = -.008$ ($p < .05$); Time 5, $B = -.010$ ($p < .01$); Time 6, $B = -.012$ ($p <.01$). This indicates that gender dissimilarity has initially no effect on absenteeism but leads to higher absenteeism later on. This is also illustrated by Figure 2, where we plotted the temporal patterning of the conditional, unit-specific effect on absenteeism for female and male employees of being in a team with a low share of women (-1SD from the mean, which equals 15.8% women) or a high share of women (+1SD, which equals 67.3% women). In sum, these results lend support to Hypothesis 1a.

------- *Insert Table 2 about here* -------

------- *Insert Figure 2 about here* -------

Moreover, the shape of the interaction displayed in Figure 2 is in line with Hypothesis 2a, as it indicates that dissimilar women have a steeper absenteeism trajectory and accordingly higher absolute absenteeism levels during later observational periods than do their dissimilar male counterparts. To test whether the effect of dissimilarity differs significantly between men and women, a slope difference test is required. However, slope difference tests for three-way interactions are not defined in a negative binomial GLMM. We therefore adapted the procedure of Meyer, Shemla, Li, and Wegge (2015) and approximated the slope difference via nonparametric bootstrapping, with 1,000 estimates for the conditional slope when dissimilar individuals were female and 1,000 estimates of the conditional slope when dissimilar individuals were male. This provided us with 1,000 estimates of the slope difference between dissimilar women and men (M_B = *.103, SD_B = .015*), which turned out to be significant (z = 218.035, p < .001), thereby lending support to Hypothesis 2a. Still, we found a significant gender dissimilarity effect also for men, as an additional slope difference test revealed that the slope for men with high dissimilarity was significantly steeper than for men with low dissimilarity (M_B = .012, SD_B = .007, z = 155.138, p < .001).

Next, we performed the same set of analyses for age dissimilarity to put Hypotheses 1b and 2b to the test. The results are depicted in Model 4 of Table 2. The interaction age × group age composition × time was significant (B = -.001, p < .001; RR = .999), indicating that the effect of age dissimilarity varies over time. To further inspect how it varies, we tested whether the effect of age dissimilarity on absenteeism increases over time by centering the time variable at each of the seven time-points. (Again, the interaction as reported here indicates similarity effects; dissimilarity effects can be obtained by sign reversal.) We found no consistent pattern in the development of the age dissimilarity effect over time, as higher age dissimilarity meant lower absenteeism during Time 0 and Time 1 (age × group age composition: Time 0 B = .003, p < .001; Time 1 B = .002, p < .01), then had no significant effect from Time 2 to Time 4 (age × group age composition: Time 2 B = .001, p = .098;Time 3 B = .000, p = .948; Time 4 B = -.001, p = .126), and at Times 5 and 6 led to significantly higher absenteeism values (age × group age composition: Time 5 B = -.002, p < .05; Time 6, B = -.003, p < .01). Accordingly, Hypothesis 1b is not confirmed.

The reason for this unexpected finding becomes apparent when the temporal patterning of the conditional, unit-specific absenteeism trajectory is plotted for young employees (-1SD from mean, which equals 32.5 years) and old employees (+1SD from mean, which equals 54.6 years) in teams with high average age (+1SD from mean, which equals 50.1 years) and low average age (-1SD from mean, which equals 41.9 years), respectively. As can be seen in Figure 3, the age dissimilarity effect behaves as expected only for older employees, where higher age dissimilarity leads to higher absenteeism particularly at later stages. In contrast, age dissimilarity has a different effect for young employees: it has larger effects initially than later, and dissimilar young employees have lower absenteeism levels throughout the observation period. This result is also supported by slope difference tests, where we find a significant larger positive slope for dissimilar old employees than for dissimilar young employees ($M_B = .036, SD_B = .003; z = 348.32$, $p < .001$). Accordingly, Hypothesis 2b is supported.

------- *Insert Figure 3 about here* -------

DISCUSSION

Much has been learned about the effects of demographic dissimilarity on withdrawal behaviors, but almost all knowledge is based on static theorizing and research designs. In this research, we built on and integrate ideas from the social identity approach (Haslam, 2011) and anchoring events theory (Ballinger & Rockmann, 2010) to develop a theoretical model for understanding how the effect of individual-level demographic dissimilarity unfolds over time on absenteeism behavior and what factors shape the unfolding process. We theorize that demographically dissimilar team members are likely to perceive negative anchoring events due to their out-group status which taint all further evaluations of social interactions with the majority team members. This is expected to result in an accumulation of perceptions of negative social relationships (i.e., discriminatory treatment and exclusion), ultimately leading to increasing levels of absenteeism over time. Moreover, we add that this effect is to be most pronounced for women and older individuals because they are often subject to salient stereotypes and a mismatch between stereotypes and the job prototype in our blue-collar setting and accordingly are most likely to perceive negative anchoring events. The results from our study largely confirm our hypotheses: we document an increase in absenteeism behavior over time, as more demographically dissimilar individuals react only after some years of exposure to being "different" from their teammates. Moreover, this increase is steepest for women and older employees.

Theoretical Implications

Our theoretical model and empirical results contribute to the literatures on relational demography and diversity in at least three ways. First, we extend previous theories of relational demography by integrating anchoring events theory (Ballinger & Rockmann, 2010) with social identity arguments (Haslam, 2011) so as to account theoretically for the dynamics of the dissimilarity effect. We suggest intensifying effects of relational demography over time because negative categorization events set an anchor and lead to, potentially biased, perceptions of repeated discrimination and social exclusion in subsequent encounters with the dissimilar majority on the team. Our theoretical framework takes up the idea of intensifying negative intergroup relations recently raised by Srikanth et al. (2016) and answers the authors' calls for more research on the disintegration of interpersonal relations in diverse teams over time. Our empirical results document such disintegration, as we find higher absenteeism of dissimilar individuals, particularly after some time on the team. In that way our research questions the universal applicability of social contact arguments to dissimilarity research. While we do not question that under some circumstances demographic differences might lose importance over time (for details see our managerial implications section), in many circumstances emotions and biases involved in evaluations may prevent majority members from recategorizing dissimilar individuals and stand in the way of normalizing relationships (Ballinger & Rockmann, 2010).

Our reasoning and findings well align with arguments which have explicitly or implicitly questioned the broad applicability of social contact arguments to dissimilarity research. For instance, Chatman, Polzer, Barsade, and Neale (1998) argue that demographically different team members are likely to experience difficulties in communicating different perspectives and therefore in supporting each other. Similarly, Ellemers and Jetten (2013: 4) have pointed out that the conceptualization of marginalized newcomers as "core members in waiting" cannot explain why their loyalty becomes less reliable over time and their individual goals become more discrepant from their groups' goals. While our theory as well as our empirical findings address this criticism and explain why dissimilar individuals disintegrate from teams over time, our research is not intended to be the last word in the debate about the temporal effect of demographic differences. Thus, we challenge researchers to further explore dynamic effects of demographic dissimilarity in temporal settings.

Second, our findings on the time-varying effects of demographic dissimilarity may also explain inconsistent results in past relational demography research. Qualitative and quantitative reviews have reported inconsistent and small average effects of demographic dissimilarity on individual withdrawal behaviors (Guillaume et al., 2012; Riordan, 2000). In a similar vein, studies have noted inconsistent findings for the asymmetric effects of demographic differences as low-status groups, like women and older employees, have not always been found to react particularly negatively to their minority status in a work group (e.g., Chattopadhyay, 1999; Jansen, van den Bosch, & Volberda, 2006). While the proposition that dissimilarity effects are asymmetric due to status difference of demographic groups is not unique to our study (Chattopadhyay et al., 2008), we are among the first to examine when those asymmetric effects occur. Our blue-collar sample provides a setting where we would expect to see particularly strong asymmetric effects because the low status of women and older workers might be particularly salient given that the job prototype of the physical blue-collar work stands in sharp contrast to commonly held stereotypes towards women or older workers (Kulik et al., 2016; Perry, 1994). Yet, even in our blue-collar setting we find that asymmetric dissimilarity effects are not always observable but surface only after some years of exposure to dissimilarity. Accordingly, our ability to identify the asymmetries hinges on the chosen time-frame to study dissimilarity effects. If our study had simply examined the effect of relational demography at one point of time for individuals at different stages of team membership, this development may have been missed. Accordingly, our study provides further, more nuanced evidence in support of the idea that "not all demographic... dissimilarity is created equal" (Guillaume, van Knippenberg, & Brodbeck, 2014: 1300).

Third, our study also contributes to team-level diversity research, as the asymmetric effects of demographic differences elucidate the micro-dynamics in diverse teams below the team level. Researchers have repeatedly called for a multilevel perspective in the study of team-level diversity (Joshi et al., 2011). Most notably, van Dijk et al. (2017) argued that a better, more time-sensitive understanding of team-level diversity effects requires an understanding of individual-level consequences of social category membership. We took steps in this direction and demonstrated that longitudinal effects of dissimilarity play out differently depending on the demographic group membership. Specifically, we found women and older employees to react more strongly to dissimilarity compared with men and younger employees. In this regards, our findings might also explain why the few team-level studies on the time-variant effects of diversity (Acar, 2010; Harrison et al., 1998; Harrison et al., 2002; Mohammed & Angell, 2004) have revealed a mixture of time-stable and time-variant effects of diversity on team outcomes (leaving aside their lack of longitudinal data to reliably estimate such time-variant effects). The exclusive reliance on team-level processes and outcomes in diversity studies might have limited a more nuanced understanding of diversity effects, as it concealed differential temporal effects on certain members of the team. In consequence, we encourage researchers interested in the temporal effects of team diversity to place more focus on differential effects at the individual level and how they feed into team-level processes.

Strengths, Limitations, and Directions for Future Research

This study has some notable methodological strengths: objective data covering all individuals in a large business unit over seven years, a theoretically meaningful starting point for our analysis defined by team entry, and up-to-date statistical methods accommodating the longitudinal data structure and the distributional properties of the absence variable. Still, our research has several limitations that suggest avenues for future research.

First, although the evidence is consistent with our general theoretical prediction, as we found more strongly increasing absenteeism and, accordingly, higher absolute levels of absenteeism for dissimilar female and older employees, we observed a different pattern for dissimilar young employees. They had lower absenteeism than their more similar young colleagues throughout the whole observational period. A potential explanation resides in the different motives that individuals favor in different life stages introduced by the socioemotional selectivity theory (Carstensen, 1992). The main argumentation is that all adults experience a shift from an open-ended to a closed time perspective when they realize that their lifetime is limited. As long as mostly younger individuals have an open-ended time perspective, they are more willing to invest in long-term instrumental goals, such as making a career despite the challenges of being socially distant from other team members. In contrast, people who perceive a limited future typically will strive for more short-term rewards, such as positive emotions in social relationships. Older employees might thus be more prone to avoid emotionally unpleasant situations by being physically absent. We encourage further research to test this possibility.

Second, while our evidence is consistent with our theoretical prediction derived from social identity and anchoring events theories, we can only infer the underlying process and cannot directly test it. In our theorizing we argue that significant negative interactions between the dissimilar individual and the majority in the team function as anchoring events and bias all subsequent interactions. While cross-sectional research provides evidence that demographically dissimilar individuals indeed experience lower social integration (for a meta-analysis, see Guillaume et al., 2012) and perceive more discriminatory treatment (Avery et al., 2008), it would have been interesting to study the anchoring events and their effects more directly. In consequence, we undertook some empirical post-hoc analyses using information from the organization's annual employee survey, to which we got access at the aggregated team level. We created a data set for all 820 teams of our main analyses. To avoid nonresponse bias, we imputed missing information with the expectation-maximization (EM) algorithm. To measure potential negative anchoring events in teams with dissimilar newcomers, we used an item from the employee survey tapping mutual team support ("*In our team we support each other during our work*"). To assess the amount of dissimilarity of female and older newcomers on the team level, we created an interactive term that multiplied the proportion of female (or aged 40+) newcomers among all newcomers by the proportion of female (or aged 40+) team members at T_0. A high value of this variable signifies similarity of the newcomers (i.e., there is a high proportion of similar female/older team members to lower the out-group categorization of the newcomers), whereas a low value signifies dissimilarity (i.e., there is a low proportion of similar female/older team members to increase the out-group categorization of the newcomers). Then we regressed this variable on the mutual team support measure at T_1, while controlling for the main effects of percentage of female (or aged 40+) newcomers at T_0 as well as the mutual team support measure from T_0. The time-lagged regression results show that the newcomer (dis)similarity measure had significant relations to the average perceptions of team support in teams with female ($B = .58$, $p < .01$) and older newcomers ($B = .80$, $p < .05$). Furthermore, dissimilarity related significantly to the variance of the team support measure, assessed through the coefficient of variation (*SD*/mean), in teams with female ($B = -.01$, $p < .01$) and older newcomers ($B = -.01$, $p < .05$). These post-hoc results imply that, in line with our theoretical assumptions, the average perception of mutual team support—as proxy for potential negative anchoring events—is lower in teams where the newcomers are demographically dissimilar than in teams where the newcomers are similar to the existing members. Although these further analyses do not directly tap individual perceptions of negative anchoring events, they strengthen our core assumption that negative anchoring events may indeed occur early in the team memberships of demographically dissimilar newcomers. Still, we encourage future work to assess individual perceptions of anchoring events in diary studies of newcomers.

Third, the generalizability of our findings might be somewhat limited because they are based on blue-collar workers employed in one organization in Switzerland. Thus future research should try to replicate our findings in other contexts. Such replication efforts might involve white-collar employees from different firms, industries, and/or countries. In particular, white-collar samples with weaker job prototypes and more sophisticated and extensive staffing procedures might reduce the likelihood of dissimilarity-related negative anchoring events. The strong effects of gender and age dissimilarity may have been promoted by our relatively low-skilled blue-collar setting, where gender and age often indicate social status and skill-based status indicators (e.g., educational degree) may be less available (Perry, Kulik, & Zhou, 1999).

Fourth, we focused only on surface-level demographic attributes in this study and thus did not test the hypothesis introduced by Harrison et al. (1998) that surface-level attributes lose their importance over time in favor of deep-level diversity attributes (personality, values, etc.). Interestingly, we showed that surface-level characteristics have, in contrast to the conventional wisdom in this literature, a very long-lasting impact on absenteeism trajectories. However, as our archival data set provided no information on deep-level diversity facets, we encourage future studies to consider their competing and interactive effects with those of surface-level characteristics on absenteeism over time and to inspect, for example, whether similarity in deep-level attributes can compensate for the negative anchoring events caused by superficial dissimilarities.

Fifth, following previous research in the relational demography tradition, we controlled for age when studying gender dissimilarity effects and vice versa, but we did not directly examine whether the influence of dissimilarity on a particular demographic dimension depends on another demographic dimension (e.g., whether the effect of gender dissimilarity hinges on the person's age dissimilarity). Arguments from the intersectionality and social complexity literature propose that different demographic attributes combine and jointly influence stereotyping (Hall et al., in press), and our theoretical reasoning would suggest that older women deviate most from the blue-collar job prototype and thus would be most likely to perceive negative anchoring events and exhibit increasing absenteeism. To check for this possibility, we extended our final model and included a five-way interaction term between individual gender, share of women, individual age, average age, and time, as well as all two-, three-, and four-way interactions of those variables. The five-way interaction did not turn out to be significant (B = -.000; p = .423).

However, this finding might be caused by measurement issues, as the five-way interaction has low statistical power (Aguinis, Edwards, & Bradley, 2017). Accordingly, we encourage future research to develop better multidimensional dissimilarity measures like those already available for team-level faultlines research (Meyer & Glenz, 2013).

Besides the limitations, this study does offer avenues for future research. One route would be to extend the criterion space when studying the dynamic effects of relational demography. Researchers might look at performance-related outcomes (e.g., task performance, creativity) or other forms of withdrawal (e.g., turnover, lateness). It might be particularly interesting to investigate whether lateness directly affects absenteeism, and absenteeism in turn affects turnover (Berry, Lelchook, & Clark, 2012). Such a progression perspective rests on the idea of withdrawal as a process characterized by increasing absenteeism and lateness trajectories and the end point of this gradual process marked by the termination of employment in the respective company. Accordingly, we would expect that quitting is likeliest, not necessarily for the individuals with the highest absolute absenteeism or lateness levels in a single year, but for those whose absenteeism and lateness have increased constantly over a longer time. This would be in line with an emerging research trend which argues that turnover intention is determined not only by an absolute measure of attitude toward the job but by the gestalt of the attitude profile over time (e.g., Zhu et al., 2017).

Managerial Implications

During the last years, many companies have started diversity initiatives, which mostly center around diversity-friendly recruitment strategies (Kulik & Roberson, 2008). In SHRM's Workplace Diversity Practice Survey Report (2010), 79% of HR professionals surveyed reported the use of such strategies, making this the most highly ranked diversity practice. The underlying idea may be that, as soon as the number of underrepresented demographic group members increases in organizations, more frequent interactions across differences, repeated over time, will result in mutual acceptance (see Harrison et al., 1998 for a similar argument). Assuming that equal representation of demographic groups is a long process and demographic dissimilarity will continue to exist at least in subunits for the foreseeable future, our findings suggest that such expectations are overly optimistic. Rather, the strategy of focusing only on diversity-friendly recruitment and leaving all else to the course of time might backfire. We found indications that women and older employees who are clearly outnumbered by dissimilar others react with stereotype-confirming behavior—lower attachment in the form of increasing absenteeism over time.

The increasing absenteeism of more dissimilar individuals in our blue-collar setting is also highly relevant for companies from a financial perspective. A woman who moves from a team with a share of women 1 SD above the mean to a team with a share of women 1 SD below the mean is absent 6.3 days more over the seven years, which (given an eight-hour workday) equals 50.2 work-hours. At the average labor cost for blue-collar workers in the sample organization, this costs the company 2,555.87 Swiss francs ($2,576.32) for a single woman. For older employees the comparable figures (based on moving from a team with an average age 1 SD above the mean to a team with an average age 1 SD below the mean) are 8.4 days or 67.4 work-hours, costing 3,437.52 Swiss francs ($3,463.65) for a single employee.

While our theory and results suggest that dissimilar workers, particularly when being female or old, are on average more absent over time, companies should not expect such increases for all dissimilar individuals. Even in our blue-collar context with strong job prototypes favoring negative anchoring events related to gender and age, there seems to be some leeway for effective interventions. For instance, we found that even in teams with a low (-1*SD* below the mean) share of women, 25% of female newcomers did not increase their absences over the observation period (as shown by the Bayes slope estimates of the baseline analysis). What makes these women immune from the trend, and how can companies intervene to avoid the emergence of negative anchoring events and thus of increasing absenteeism?

Some characteristics of our sample (i.e., lack of systematic staffing and socialization procedures), as well as past research findings on diversity-friendly climates and leadership, suggest that companies should attend to the temporal patterning of demographic dissimilarity effects and complement their diversity-friendly recruitment strategies in at least three ways. First, companies might consider using structured recruitment and transfer processes also for low-skilled blue-collar jobs and internal hires (Keller, 2017). Involving the supervisor and potentially also the other members of the recipient team in newcomer selection might heighten their sensitivity to successful integration of demographically dissimilar newcomers and lower the risk of perceptions of negative anchoring events for the newcomers.

Second, companies should reflect critically on their socialization tactics for newcomers. While institutionalized socialization tactics (clear formal and informal introductions to the norms, rules, and relationships in the new work setting) are often used in high-skilled environments, such as technical positions (for a review, see Chandler, Kram, & Yip, 2011), our research suggests that organizations should also aim at smooth transitions for dissimilar low-skilled blue-collar workers. Formal mentoring from an experienced team member might help newcomers get better integrated into the core structure and identity of the team (Payne & Huffman, 2005; Ragins, 1997), thereby reducing out-group positioning that often causes perceptions of negative anchoring events.

Third, cross-sectional research suggests that the likelihood of perceived negative treatment of a demographically dissimilar individual may be reduced when the team climate is inclusive and the leader develops intense relationships with the individual. Inclusive climates might be achieved through diversity training, which has been shown to be effective in blue-collar as well as white-collar samples (Bezrukova, Jehn, & Spell, 2012; Meuse, Hostager, & O'Neill, 2007; Reynolds, 2010). In addition, leadership has been shown to be central in smoothing relations between demographic groups (Guillaume, Dawson, Otaye-Ebede, Woods, & West, 2017). One particularly relevant leadership behavior might be high leader-member exchange (LMX) (Graen & Uhl-Bien, 1995) between the dissimilar individual and the supervisor, as it is one way to signal that the supervisor is willing and able to go beyond expectations to facilitate positive interaction with the individual. Past research confirms that members of teams with both supportive/valuing climates and high LMX perceive higher team-member exchange (TMX)—a general positive exchange relationship among the team members (Tse, Dasborough, & Ashkanasy, 2008). Hence, we suggest that inclusive climates and positive exchange relationships with the supervisor might contribute their part to higher quality exchange relationships between dissimilar team members and lower risks of perceived negative anchoring events.

CONCLUSION

Following repeated calls for more dynamic research, the present study builds and extends theory in relational demography research. Drawing on the social identity approach and anchoring events theory, we develop predictions about the temporal patterning of demographic dissimilarity effects on absenteeism. Although we cannot fully test the core underlying theoretical mechanism, our findings reveal that demographic dissimilarity, particularly for women and older employees, has no immediate or constant effect on absenteeism but increases it in the long run. The present article helps in moving the study of relational demography and diversity to a more dynamic — and arguably more realistic—perspective and we encourage more dynamic research in this area.

REFERENCES

Acar, F. P. 2010. Analyzing the effects of diversity perceptions and shared leadership on emotional conflict: A dynamic approach. ***The International Journal of Human Resource Management***, 21(10): 1733–1753.

Aguinis, H., Edwards, J. R., & Bradley, K. J. 2017. Improving Our Understanding of Moderation and Mediation in Strategic Management Research. ***Organizational Research Methods***, 20(4): 665–685.

Aiken, L. S., Mistler, S. A., Coxe, S., & West, S. G. 2015. Analyzing count variables in individuals and groups: Single level and multilevel models. ***Group Processes & Intergroup Relations***, 18(3): 290–314.

Allport, G. W. 1954. ***The nature of prejudice***. Reading, Mass.: Addison-Wesley Pub. Co.

Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. 2010. On making causal claims: A review and recommendations. ***The Leadership Quarterly***, 21(6): 1086–1120.

Atkins, D. C., Baldwin, S. A., Zheng, C., Gallop, R. J., & Neighbors, C. 2013. A tutorial on count regression and zero-altered count models for longitudinal substance use data. ***Psychology of Addictive Behaviors : Journal of the Society of Psychologists in Addictive Behaviors***, 27(1): 166–177.

Avery, D. R., McKay, P. F., & Wilson, D. C. 2008. What are the odds? How demographic similarity affects the prevalence of perceived employment discrimination. ***Journal of Applied Psychology***, 93(2): 235–249.

Bacharach, S. B., Bamberger, P., & Biron, M. 2010. Alcohol consumption and workplace absenteeism: the moderating effect of social support. ***Journal of Applied Psychology***, 95(2): 334–348.

Bakker, A. B., Demerouti, E., Boer, E. de, & Schaufeli, W. B. 2003. Job demands and job resources as predictors of absence duration and frequency. ***Journal of Vocational Behavior***, 62(2): 341–356.

Ballinger, G. A., & Rockmann, K. W. 2010. Chutes Versus Ladders: Anchoring Events and a Punctuated-Equilibrium Perspective on Social Exchange Relationships. ***Academy of Management Review***, 35(3): 373–391.

Berger, J., M., Hamit, F., Robert, Z. N., & Morris, Z. 1977. ***Status Characteristics and Social Interaction: An Expectations-States Approach***. New York: Elsevier.

Berry, C. M., Lelchook, A. M., & Clark, M. A. 2012. A meta-analysis of the interrelationships between employee lateness, absenteeism, and turnover: Implications for models of withdrawal behavior. ***Journal of Organizational Behavior***, 33(5): 678–699.

Bezrukova, K., Jehn, K. A., & Spell, C. S. 2012. Reviewing Diversity Training: Where We Have Been and Where We Should Go. ***Academy of Management Learning & Education***, 11(2): 207–227.

Biron, M., & Bamberger, P. 2012. Aversive workplace conditions and absenteeism: Taking referent group norms and supervisor support into account. ***Journal of Applied Psychology***, 97(4): 901–912.

Bishara, A. J., & Hittner, J. B. 2012. Testing the significance of a correlation with nonnormal data: Comparison of Pearson, Spearman, transformation, and resampling approaches. ***Psychological Methods***, 17(3): 399–417.

Blevins, D. P., Tsang, E. W. K., & Spain, S. M. 2015. Count-Based Research in Management: Suggestions for Improvements. ***Organizational Research Methods***, 18(1): 47–69.

Bliese, P. D., & Ployhart, R. E. 2002. Growth Modeling Using Random Coefficient Models: Model Building, Testing, and Illustrations. ***Organizational Research Methods***, 5(4): 362–387.

Brown, D., Dickens, R., Gregg Paul, Machin, S., & Manning, A. 2001. ***Everything under a fiver***: ***Recruitment and retention in lower paying labour markets.*** Richard Dickens, Paul Gregg, Stephen Machin and. York: YPS.

Carstensen, L. L. 1992. Social and emotional patterns in adulthood: Support for socioemotional selectivity theory. ***Psychology and Aging***, 7(3): 331.

Chandler, D. E., Kram, K. E., & Yip, J. 2011. An ecological systems perspective on mentoring at work: A review and future prospects. ***Academy of Management Annals***, 5(1): 519–570.

Chatman, J. A., & Flynn, F. J. 2001. The Influence of Demographic Heterogeneity on the Emergence and Consequences of Cooperative Norms in Work Teams. ***Academy of Management Journal***, 44(5): 956–974.

Chatman, J. A., Polzer, J. T., Barsade, S. G., & Neale, M. A. 1998. Being Different Yet Feeling Similar: The Influence of Demographic Composition and Organizational Culture on Work Processes and Outcomes. ***Administrative Science Quarterly***, 43(4): 749.

Chatman, J. A., & Spataro, S. E. 2005. Using Self-Categorization Theory to Understand Relational Demography–Based Variations in People's Responsiveness to Organizational Culture. ***Academy of Management Journal***, 48(2): 321–331.

Chattopadhyay, P. 1999. Beyond Direct and Symmetrical Effects: The Influence of Demographic Dissimilarity on Organizational Citizenship Behavior. ***Academy of Management Journal***, 42(3): 273–287.

Chattopadhyay, P., George, E., & Shulman, A. D. 2008. The Asymmetrical Influence of Sex Dissimilarity in Distributive vs. Colocated Work Groups. ***Organization Science***, 19(4): 581–593.

Chattopadhyay, P., Tluchowska, M., & George, E. 2004. Identifying the ingroup: A closer look at the influence of demographic dissimilarity on employee social identity. ***Academy of Management Review***, 29(2): 180–202.

Conway, M. A., & Pleydell-Pearce, C. W. 2000. The construction of autobiographical memories in the self-memory system. ***Psychological Review***, 107(2): 261–288.

Cronin, M. A., Weingart, L. R., & Todorova, G. 2011. Dynamics in Groups: Are We There Yet? ***Academy of Management Annals***, 5(1): 571–612.

David, E. M., Avery, D. R., Witt, L. A., & McKay, P. F. 2015. A time-lagged investigation of the impact of coworker behavior on the effects of demographic dissimilarity. ***Journal of Organizational Behavior***, 36(4): 582–606.

Dello Russo, S., Miraglia, M., Borgogni, L., & Johns, G. 2013. How time and perceptions of social context shape employee absenteeism trajectories. ***Journal of Vocational Behavior***, 83(2): 209–217.

Dwertmann, D. J. G., & Boehm, S. A. 2016. Status Matters: The Asymmetric Effects of Supervisor–Subordinate Disability Incongruence and Climate for Inclusion. ***Academy of Management Journal***, 59(1): 44–64.

Edwards, J. R. 1994. The Study of Congruence in Organizational Behavior Research: Critique and a Proposed Alternative. ***Organizational Behavior and Human Decision Processes***, 58(1): 51–100.

Ellemers, N. 2018. Gender Stereotypes. ***Annual Review of Psychology***, 69: 275–298.

Ellemers, N., & Jetten, J. 2013. The many ways to be marginal in a group. ***Personality and Social Psychology Review***, 17(1): 3–21.

Farrell, D., & Stamm, C. L. 1988. Meta-Analysis of the Correlates of Employee Absence. ***Human Relations***, 41(3): 211–227.

Finkelstein, L. M., Burke, M. J., & Raju, M. S. 1995. Age discrimination in simulated employment contexts: An integrative analysis. ***Journal of Applied Psychology***, 80(6): 652–663.

Fiske, S. T. 1998. Stereotyping, prejudice, and discrimination. In D. T. Gilbert, S. T. Fiske & G. Lindzey (Eds.), ***The handbook of social psychology***: 357–411. Hoboken, NJ: Oxford University Press.

Glick, P., Wilk, K., & Perreault, M. 1995. Images of occupations: Components of gender and status in occupational stereotypes. ***Sex Roles***, 32(9-10): 565–582.

Gordon, R. A., & Arvey, R. D. 2004. Age Bias in Laboratory and Field Settings: A Meta-Analytic Investigation1. ***Journal of Applied Social Psychology***, 34(3): 468–492.

Graen, G. B., & Uhl-Bien, M. 1995. Relationship-based approach to leadership: Development of leader-member exchange (LMX) theory of leadership over 25 years: Applying a multi-level multi-domain perspective. ***The Leadership Quarterly***, 6(2): 219–247.

Graf, S., Paolini, S., & Rubin, M. 2014. Negative intergroup contact is more influential, but positive intergroup contact is more common: Assessing contact prominence and contact prevalence in five Central European countries. ***European Journal of Social Psychology***, 44(6): 536–547.

Groves, R. M. 2004. ***Survey methodology***. Hobroken, NJ: John Wiley.

Guillaume, Y. R. F., Brodbeck, F. C., & Riketta, M. 2012. Surface- and deep-level dissimilarity effects on social integration and individual effectiveness related outcomes in work groups: A meta-analytic integration. ***Journal of Occupational and Organizational Psychology***, 85(1): 80–115.

Guillaume, Y. R. F., Dawson, J. F., Otaye-Ebede, L., Woods, S. A., & West, M. A. 2017. Harnessing demographic differences in organizations: What moderates the effects of workplace diversity? ***Journal of Organizational Behavior***, 38(2): 276–303.

Guillaume, Y. R. F., van Knippenberg, D., & Brodbeck, F. C. 2014. Nothing Succeeds Like Moderation: A Social Self-Regulation Perspective on Cultural Dissimilarity and Performance. ***Academy of Management Journal***, 57(5): 1284–1308.

Gundry, L. K., & Rousseau, D. M. 1994. Critical Incidents in Communicating Culture to Newcomers: The Meaning is the Message. ***Human Relations***, 47(9): 1063–1088.

Hall, E., Hall, A. V., Galinsky, A., & Phillips, K. W. in press. MOSAIC: A Model of Stereotyping Through Associated and Intersectional Categories. ***Academy of Management Review***.

Hammer, T. H., & Landau, J. C. 1981. Methodological issues in the use of absence data. ***Journal of Applied Psychology***, 66(5): 574–581.

Harrison, D. A., & Martocchio, J. J. 1998. Time for absenteeism: A 200-year review of origins, offshoots, and outcomes. ***Journal of Management***, 24(3): 305–350.

Harrison, D. A., Price, K. H., & Bell, M. P. 1998. Beyond relational demography: Time and the effects of surface- and deep-level diversity on work group cohesion. ***Academy of Management Journal***, 41(1): 96–107.

Harrison, D. A., Price, K. H., Gavin, J. H., & Florey, A. T. 2002. Time, teams, and task performance: Changing effects of surface- and deep-level diversity on group functioning. ***Academy of Management Journal***, 45(5): 1029–1045.

Haslam, S. A. 2011. ***Psychology in organizations***: ***The social identity approach*** (2nd ed.). London: Sage.

Hekman, D. R., Johnson, S. K., Foo, M.-D., & Yang, W. 2017. Does diversity-valuing behavior result in diminished performance ratings for non-white and female leaders? ***Academy of Management Journal***, 60(2): 771–797.

Hewstone, M., Rubin, M., & Willis, H. 2002. Intergroup Bias. ***Annual Review of Psychology***, 53(1): 575–604.

Hobman, E. V., & Bordia, P. 2006. The Role of Team Identification in the Dissimilarity-Conflict Relationship. ***Group Processes & Intergroup Relations***, 9(4): 483–507.

Hogg, M. A., & Terry, D. I. 2000. Social Identity and Self-Categorization Processes in Organizational Contexts. ***Academy of Management Review***, 25(1): 121–140.

Hox, J. J. 2010. ***Multilevel analysis***: ***Techniques and applications*** (2nd ed.). New York: Routledge.

Jansen, J. J. P., van den Bosch, F. A. J., & Volberda, H. W. 2006. Exploratory Innovation, Exploitative Innovation, and Performance: Effects of Organizational Antecedents and Environmental Moderators. ***Management Science***, 52(11): 1661–1674.

Jansen, W. S., Otten, S., & van der Zee, K. I. 2017. Being different at work: How gender dissimilarity relates to social inclusion and absenteeism. ***Group Processes & Intergroup Relations***, 20(6): 879–893.

Joshi, A., Liao, H., & Roh, H. 2011. Bridging Domains in Workplace Demography Research: A Review and Reconceptualization. ***Journal of Management***, 37(2): 521–552.

Judge, T. A., Piccolo, R. F., & Kosalka, T. 2009. The bright and dark sides of leader traits: A review and theoretical extension of the leader trait paradigm. ***The Leadership Quarterly***, 20(6): 855–875.

Kanter, R. M. 1977. Some Effects of Proportions on Group Life: Skewed Sex Ratios and Responses to Token Women. ***American Journal of Sociology***, 82(5): 965–990.

Kanter, R. M. 1993. ***Men and women of the corporation***. New York, NY: Basic Books.

Keller, J. 2017. Posting and Slotting: How Hiring Processes Shape the Quality of Hire and Compensation in Internal Labor Markets. ***Administrative Science Quarterly***: 1-31.

Kensinger, E. A., & Corkin, S. 2003. Memory enhancement for emotional words: Are emotional words more vividly remembered than neutral words? ***Memory & cognition***, 31(8): 1169–1180.

Klein, K. J., Dansereau, F., & Hall, R. J. 1994. Levels Issues in Theory Development, Data Collection, and Analysis. ***Academy of Management Review***, 19(2): 195–229.

Kulik, C. T., Perera, S., & Cregan, C. 2016. Engage Me: The Mature-Age Worker and Stereotype Threat. ***Academy of Management Journal***, 59(6): 2132–2156.

Kulik, C. T., & Roberson, L. 2008. Diversity initiative effectiveness: What organizations can (and cannot) expect from diversity recruitment, diversity training, and formal mentoring programs. In A. P. Brief (Ed.), ***Diversity at work***: 265–317. Cambridge: Cambridge U niversity Press.

Labianca, G., & Brass, D. J. 2006. Exploring the Social Ledger: Negative Relationships and Negative Asymmetry in Social Networks in Organizations. ***Academy of Management Review***, 31(3): 596–614.

Leslie, S.-J., Cimpian, A., Meyer, M., & Freeland, E. 2015. Expectations of brilliance underlie gender distributions across academic disciplines. ***Science***, 347(6219): 262–265.

Li, J., Meyer, B., Shemla, M., & Wegge, J. 2018. From being diverse to becoming diverse: A dynamic team diversity theory. ***Journal of Organizational Behavior***, 21(4): 1733.

Long, J. S., & Freese, J. 2014. ***Regression models for categorical dependent variables using Stata*** (3rd ed.). College Station: Stata Press Publication.

Loretto, W., & White, P. 2006. Employers' attitudes, practices and policies towards older workers. ***Human Resource Management Journal***, 16(3): 313–330.

Louis, M. R. 1980. Surprise and Sense Making: What Newcomers Experience in Entering Unfamiliar Organizational Settings. ***Administrative Science Quarterly***, 25(2): 226–251.

Markham, S. E., Dansereau, F., & Alutto, J. A. 1982. Group Size and Absenteeism Rates: A Longitudinal Analysis. ***Academy of Management Journal***, 25(4): 921–927.

Mason, C. M., & Griffin, M. A. 2003. Group absenteeism and positive affective tone: A longitudinal study. ***Journal of Organizational Behavior***, 24(6): 667–687.

Maurer, T. J., Barbeite, F. G., Weiss, E. M., & Lippstreu, M. 2008. New measures of stereotypical beliefs about older workers' ability and desire for development: Exploration among employees age 40 and over. ***Journal of Managerial Psychology***, 23(4): 395–418.

McCord, M. A., Joseph, D. L., Dhanani, L. Y., & Beus, J. M. 2018. A meta-analysis of sex and race differences in perceived workplace mistreatment. ***Journal of Applied Psychology***, 103(2): 137–163.

Meuse, K. P. de, Hostager, T. J., & O'Neill, K. S. 2007. A longitudinal evaluation of senior managers' perceptions and attitudes of a workplace diversity training program. ***Human Resource Planning***, 30(2): 38–46.

Meyer, B., & Glenz, A. 2013. Team Faultline Measures: A Computational Comparison and a New Approach to Multiple Subgroups. ***Organizational Research Methods***, 16(3): 393–424.

Meyer, B., Shemla, M., Li, J., & Wegge, J. 2015. On the Same Side of the Faultline: Inclusion in the Leader's Subgroup and Employee Performance. ***Journal of Management Studies***, 52(3): 354–380.

Mohammed, S., & Angell, L. C. 2004. Surface-and deep-level diversity in workgroups: Examining the moderating effects of team orientation and team process on relationship conflict. ***Journal of Organizational Behavior***, 25(8): 1015–1039.

Navarro, C., & Bass, C. 2006. The cost of employee absenteeism. ***Compensation & Benefits Review***, 38(6): 26–30.

Nguyen, H., Groth, M., & Johnson, A. 2013. When the Going Gets Tough, the Tough Keep Working. ***Journal of Management***, 42(3): 615–643.

Nickerson, R. S. 1998. Confirmation bias: A ubiquitous phenomenon in many guises. ***Review of General Psychology***, 2(2): 175–220.

Organization for Economic Cooperation and Development 2018. ***OECD.Stat***. Retrieved from https://stats.oecd.org/Index.aspx?DataSetCode=LFS_SEXAGE_I_R.

Payne, S. C., & Huffman, A. H. 2005. A longitudinal examination of the influence of mentoring on organizational commitment and turnover. ***Academy of Management Journal***, 48(1): 158–168.

Perry, E. 1994. A Prototype Matching Approach to Understanding the Role of Applicant Gender and Age in the Evaluation of Job Applicants1. ***Journal of Applied Social Psychology***, 24(16): 1433–1473.

Perry, E. L., Kulik, C. T., & Bourhis, A. C. 1996. Moderating effects of personal and contextual factors in age discrimination. ***Journal of Applied Psychology***, 81(6): 628–647.

Perry, E. L., Kulik, C. T., & Zhou, J. 1999. A closer look at the effects of subordinate-supervisor age differences. ***Journal of Organizational Behavior***, 20(3): 341–357.

Ployhart, R. E., & Ward, A.-K. 2011. The “Quick Start Guide” for Conducting and Publishing Longitudinal Research. ***Journal of Business and Psychology***, 26(4): 413–422.

Rabe-Hesketh, S., & Skrondal, A. 2008. ***Multilevel and longitudinal modeling using Stata*** (2nd ed.). College Station, Tex.: Stata Press.

Ragins, B. R. 1997. Diversified mentoring relationships in organizations: A power perspective. ***Academy of Management Review***, 22(2): 482–521.

Raudenbush, S. W. 2008. Many Small Groups. In J. d. Leeuw & E. Meijer (Eds.), ***Handbook of Multilevel Analysis***: 207–236. New York, NY: Springer New York.

Raudenbush, S. W., & Bryk, A. S. 2002. ***Hierarchical linear models***: ***Applications and data analysis methods*** (2nd ed.). Thousand Oaks: Sage Publications.

Reynolds, L. 2010. Aging and disability awareness training for drivers of a metropolitan taxi company. ***Activities, Adaptation & Aging***, 34(1): 17–29.

Riordan, C. M. 2000. Relational demography within groups: Past developments, contradictions, and new directions. ***Research in Personnel and Human Resources Management***: 131–173.

Riordan, C. M., Schaffer, B. S., & Stewart, M. M. 2005. Relational demography within groups: Through the lens of discrimination. In R. L. Dipboye & A. Colella (Eds.), ***Discrimination at work. The psychological and organizational bases***: 37–62. Mahwah, N.J.: Lawrence Erlbaum Associates, Publishers.

Riordan, C. M., & Wayne, J. H. 2008. A Review and Examination of Demographic Similarity Measures Used to Assess Relational Demography Within Groups. ***Organizational Research Methods***, 11(3): 562–592.

Roberson, Q. M. 2006. Justice in teams: The activation and role of sensemaking in the emergence of justice climates. ***Organizational Behavior and Human Decision Processes***, 100(2): 177–192.

Roth, L. M. 2004. The Social Psychology of Tokenism: Status and Homophily Processes on Wall Street. ***Sociological Perspectives***, 47(2): 189–214.

Sacco, J. M., & Schmitt, N. 2005. A dynamic multilevel model of demographic diversity and misfit effects. ***Journal of Applied Psychology***, 90(2): 203–231.

Saks, A. M., & Ashforth, B. E. 1997. Organizational Socialization: Making Sense of the Past and Present as a Prologue for the Future. ***Journal of Vocational Behavior***, 51(2): 234–279.

Shadish, W. R., Cook, T. D., & Campbell, D. T. 2002. ***Experimental and quasi-experimental designs for generalized causal inference***. Belmont, CA: Wadsworth Cengage Learning.

Shah, P. P. 1998. Who Are Employees' Social Referents?: Using a Network Perspective to Determine Referent Others. ***Academy of Management Journal***, 41(3): 249–268.

SHRM 2010. ***Workplace Diversity Practices: How Has Diversity and Inclusion Changed Over Time?***: ***A Comparative Examination: 2010 and 2005***.

Singer, J. D., & Willett, J. B. 2003. ***Applied longitudinal data analysis***: ***Modeling change and event occurrence***. New York, Oxford: Oxford University Press.

Skrondal, A., & Rabe-Hesketh, S. 2008. Multilevel and Related Models for Longitudinal Data. In J. d. Leeuw & E. Meijer (Eds.), ***Handbook of Multilevel Analysis***: 275–299. New York, NY: Springer New York.

Solinger, O. N., van Olffen, W., Roe, R. A., & Hofmans, J. 2013. On Becoming (Un)Committed: A Taxonomy and Test of Newcomer Onboarding Scenarios. ***Organization Science***, 24(6): 1640–1661.

Srikanth, K., Harvey, S., & Peterson, R. 2016. A Dynamic Perspective on Diverse Teams: Moving from the Dual-Process Model to a Dynamic Coordination-based Model of Diverse Team Performance. ***Academy of Management Annals***, 10(1): 453–493.

Swiss Federal Statistical Office 2018. ***Berufshauptgruppen ISCO-08 nach Geschlecht, Nationalität, Altersgruppen, Familientyp.*** (Job Types ISC0-8 by Gender, Nationality, Age, Family Status). Retrieved from https://www.bfs.admin.ch/bfs/de/home/statistiken/kataloge-datenbanken/tabellen.assetdetail.5246827.html.

Tajfel, H., & Turner, J. C. 1986. Social identity theory and intergroup behavior. In W. G. Austin & S. Worchel (Eds.), ***Psychology of intergroup relations***: 518–538 (2nd ed.). Chicago: Nelson-Hall Publishers.

Tse, H. H.M., Dasborough, M. T., & Ashkanasy, N. M. 2008. A multi-level analysis of team climate and interpersonal exchange relationships at work. ***The Leadership Quarterly***, 19(2): 195–211.

Tsui, A. S., Egan, T. D., & O'Reilly, C. A. 1992. Being Different: Relational Demography and Organizational Attachment. ***Administrative Science Quarterly***, 37(4): 549–579.

Tsui, A. S., & Gutek, B. A. 1999. ***Demographic differences in organizations***: ***Current research and future directions***. Lanham, MD. [etc.]: Lexington Books.

Turco, C. J. 2010. Cultural foundations of tokenism: Evidence from the leveraged buyout industry. ***American Sociological Review***, 75(6): 894–913.

Turner, J. C. 1987. A self-categorization theory. In J. C. Turner (Ed.), ***Rediscovering the social group. A self-categorization theory***: 42–67. Oxford: Blackwell.

van Dijk, H., Meyer, B., van Engen, M., & Loyd, D. L. 2017. Microdynamics in Diverse Teams: A Review and Integration of the Diversity and Stereotyping Literatures. ***Academy of Management Annals***, 11(1): 517–557.

Wang, M. O., Zhan, Y., McCune, E., & Truxillo, D. 2011. Understanding newcomers' adaptability and work-ralted outcomes: Testing the mediating roles of perceived P-E fit Variables. ***Personnel Psychology***, 64(1): 163–189.

Weiss, E. M., & Maurer, T. J. 2004. Age Discrimination in Personnel Decisions: A Reexamination. ***Journal of Applied Social Psychology***, 34(8): 1551–1562.

Williams, C. L. 1992. The glass escalator: Hidden advantages for men in the “female” professions. ***Social problems***, 39(3): 253–267.

Williams, K. D. 2007. Ostracism. ***Annual Review of Psychology***, 58.

Ybema, J. F., Smulders, P. G. W., & Bongers, P. M. 2010. Antecedents and consequences of employee absenteeism: A longitudinal perspective on the role of job satisfaction and burnout. ***European Journal of Work and Organizational Psychology***, 19(1): 102–124.

Zhu, J., Tatachari, S., & Chattopadhyay, P. 2017. Newcomer Identification: Trends, Antecedents, Moderators, and Consequences. ***Academy of Management Journal***, 60(3): 855–879.

TABLE 1 Descriptive Statistics and Correlations

	Variable	mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1	Division Dummy, time 0	.39	.49																										
2	Leadership Position, time 0	.04	.19	-.06 *																									
3	Tenure, time 0	15.40	12.65	.03	.07 *																								
4	Team Size, time 0	14.85	5.91	.13 *	-.08 *	-.01																							
5	Female, time 0	.46	.50	.10 *	-.13 *	-.41 *	.13 *																						
6	Age, time 0	43.58	11.03	.16 *	-.04	.56 *	.12 *	-.03																					
7	% Women, time 0	41.52	25.79	.28 *	-.03	-.24 *	.30 *	.53 *	.01																				
8	% Women, time 1	41.99	24.84	.24 *	-.02	-.25 *	.24 *	.54 *	.01	.95 *																			
9	% Women, time 2	42.53	24.97	.22 *	-.03	-.27 *	.26 *	.53 *	-.02	.89 *	.95 *																		
10	% Women, time 3	41.26	24.93	.17 *	-.02	-.24 *	.23 *	.52 *	.00	.84 *	.88 *	.95 *																	
11	% Women, time 4	42.74	25.10	.18 *	-.03	-.26 *	.24 *	.53 *	-.01	.80 *	.83 *	.89 *	.94 *																
12	% Women, time 5	43.65	25.59	.18 *	-.04	-.26 *	.23 *	.55 *	-.01	.76 *	.79 *	.83 *	.86 *	.94 *															
13	% Women, time 6	45.52	25.39	.20 *	-.03	-.26 *	.20 *	.52 *	-.01	.73 *	.76 *	.80 *	.82 *	.89 *	.95 *														
14	Average Age, time 0	45.97	4.10	.07 *	-.03	.25 *	.23 *	.04	.40 *	.04 *	.09 *	.06 *	.08 *	.08 *	.06 *	.07 *													
15	Average Age, time 1	46.47	4.04	.16 *	-.02	.22 *	.26 *	.03	.40 *	.04	.05 *	.00	.04	.05 *	.04	.05	.87 *												
16	Average Age, time 2	46.82	4.17	.17 *	-.04	.24 *	.16 *	.02	.39 *	.03	.03	-.01	.03	.03	-.02	.02	.74 *	.88 *											
17	Average Age, time 3	47.06	4.25	.14 *	-.03	.25 *	.14 *	.02	.40 *	.01	.03	-.02	.01	.05	.00	.07 *	.65 *	.76 *	.90 *										
18	Average Age, time 4	47.65	4.11	.19 *	-.04	.23 *	.16 *	.01	.39 *	.01	.01	-.03	.02	.00	-.02	-.01	.54 *	.64 *	.75 *	.87 *									
19	Average Age, time 5	48.01	4.10	.20 *	-.02	.22 *	.12 *	-.01	.39 *	.01	.00	-.04	-.02	-.01	-.05 *	-.05	.48 *	.54 *	.64 *	.75 *	.86 *								
20	Average Age, time 6	48.24	3.86	.17 *	-.05	.20 *	.14 *	-.01	.36 *	-.02	-.02	-.05 *	-.03	-.03	-.07 *	-.07 *	.44 *	.48 *	.55 *	.64 *	.73 *	.82 *							
21	Absemteeism, time 0	6.55	17.49	.05 *	-.04 *	.03	.02	.01	.03	.01	.00	-.01	-.03	-.01	-.02	-.01	.03	.00	.02	-.01	.03	.03	.01						
22	Absemteeism, time 1	8.77	20.16	.07 *	-.03	.03	.05 *	.05 *	.08 *	.04	.03	.03	.02	.03	.06 *	.03	.00	.02	-.01	-.03	.00	.02	-.01	.40 *					
23	Absemteeism, time 2	9.54	20.72	.03	-.03	.05 *	.05 *	.01	.06 *	.02	.02	.02	-.01	-.01	.02	.01	-.01	-.02	-.01	-.03	.03	.04	.05 *	.16 *	.28 *				
24	Absemteeism, time 3	9.07	19.60	.04	-.02	.03	.03	.01	.06 *	.02	.00	.03	.02	.03	.05	.01	.01	.00	-.02	-.03	.01	.02	.00	.09 *	.23 *	.30 *			
25	Absemteeism, time 4	9.40	21.05	.06 *	-.04	.02	.02	.04	.07 *	.03	.01	.01	.02	.02	.01	-.01	.05 *	.03	.03	.02	.03	.03	.03	.10 *	.18 *	.24 *	.38 *		
26	Absemteeism, time 5	10.54	21.17	.05 *	-.04	.03	.01	.03	.10 *	.03	.02	.03	.02	.04	.05 *	.05	.01	.02	.03	.03	.05	.02	.04	.14 *	.15 *	.20 *	.28 *	.42 *	
27	Absemteeism, time 6	10.64	22.56	.00	-.03	.03	.04	.03	.05	.02	.00	.01	.00	.00	.02	.00	-.01	.01	.01	.01	-.03	-.02	-.03	.06 *	.13 *	.13 *	.18 *	.28 *	.31*

Note: n = 1,302 - 2,711. To reduce the size of the correlation matrix correlations, for control variables are reported, only at time 0, but considered as time-variant in all analyses. The team change control variable is not reported as this variable takes a value of 0 for all observations in the first observational period. Gender and age are reported only for time 0 as they correlate perfectly with gender and age in later years.

TABLE 2 Negative Binomial Growth Curves Modeling Absenteeism Trajectories as a Function of Time and Demographic Dissimilarity

Variables	Model 1			Model 2			Model 3			Model 4		
	B	*RR*	*SE*	*B*	*RR*	*SE*	*B*	*RR*	*SE*	*B*	*RR*	*SE*
Fixed Effects												
Intercept	.845 ***	2.327	(.057)	.773 ***	2.165	(.068)	.808 ***	2.244	(.075)	.700 ***	2.014	(.071)
Division Dummy	.385 ***	1.469	(.070)	.393 ***	1.481	(.072)	.424 ***	1.528	(.074)	.397 ***	1.488	(.072)
Leadership Position	-.444 **	.642	(.140)	-.408 **	.665	(.141)	-.415 **	.660	(.141)	-.388 **	.678	(.141)
Change of Team	.040	1.041	(.070)	.039	1.039	(.070)	.039	1.040	(.070)	.034	1.035	(.070)
Tenure	.001	1.001	(.003)	.004	1.004	(.004)	.004	1.004	(.004)	.004	1.004	(.004)
Team Size	.019 ***	1.019	(.005)	.019 ***	1.019	(.005)	.018 ***	1.018	(.005)	.018 ***	1.018	(.005)
Time	.121 ***	1.129	(.012)	.126 ***	1.134	(.012)	.115 ***	1.121	(.016)	.150 ***	1.162	(.013)
Female				.177 *	1.193	(.085)	.075	1.078	(.113)	.171 *	1.186	(.085)
Age				.005	1.005	(.004)	.005	1.005	(.004)	.002	1.002	(.005)
% Women				.000	1.000	(.001)	-.001	.999	(.003)	.000	1.000	(.001)
Average Age				-.032 ***	.969	(.007)	-.031 ***	.969	(.007)	-.017	.983	(.011)
Female × % Women							.001	1.001	(.004)			
Female × Time							.055 *	1.056	(.027)			
% Women × Time							.001	1.001	(.001)			
Female × % Women × Time							-.002 *	.998	(.001)			
Age × Average Age										.003 ***	1.003	(.001)
Age × Time										.002	1.002	(.001)
Average Age × Time										-.004	.996	(.003)
Age × Average Age × Time										-.001 ***	.999	(.000)
Random Effect Variances												
Intercept	2.972			2.960			2.956			2.947		
Time	.071			.070			.070			.070		
–2 log likelihood	72141.74			72116.76 ***			72106.18 *			72092.42 ***		
AIC	72163.73			72146.77			72144.18			72130.41		

Note: N: 13,830 observations, 2,711 persons. *B* = coefficient on linear-predictor scale (i.e., log of outcome). *RR* = rate ratio (i.e., exp(B)).
***p<.001; **p<.01; *p<.05 (two-tailed).

FIGURE 1 Predicted Conditional Absenteeism Growth Trajectory from Baseline Analysis

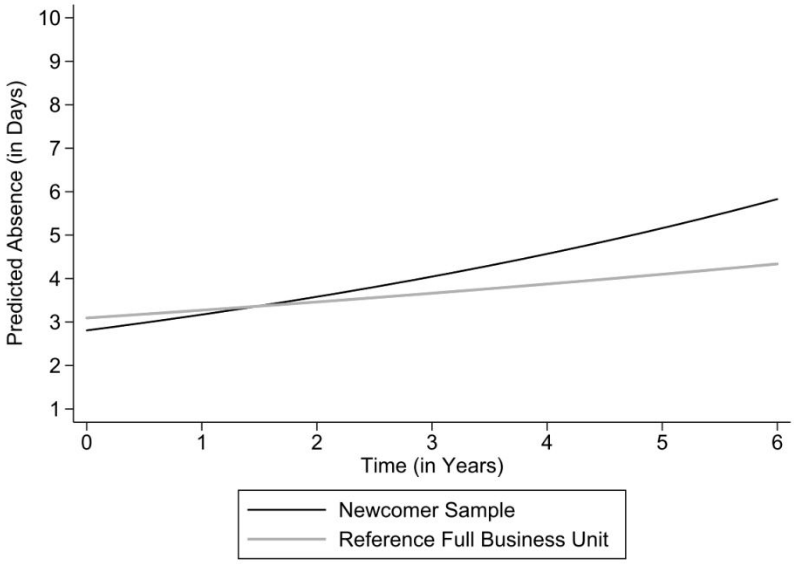


FIGURE 2 Predicted Conditional Absenteeism Growth Trajectory for Gender Dissimilarity

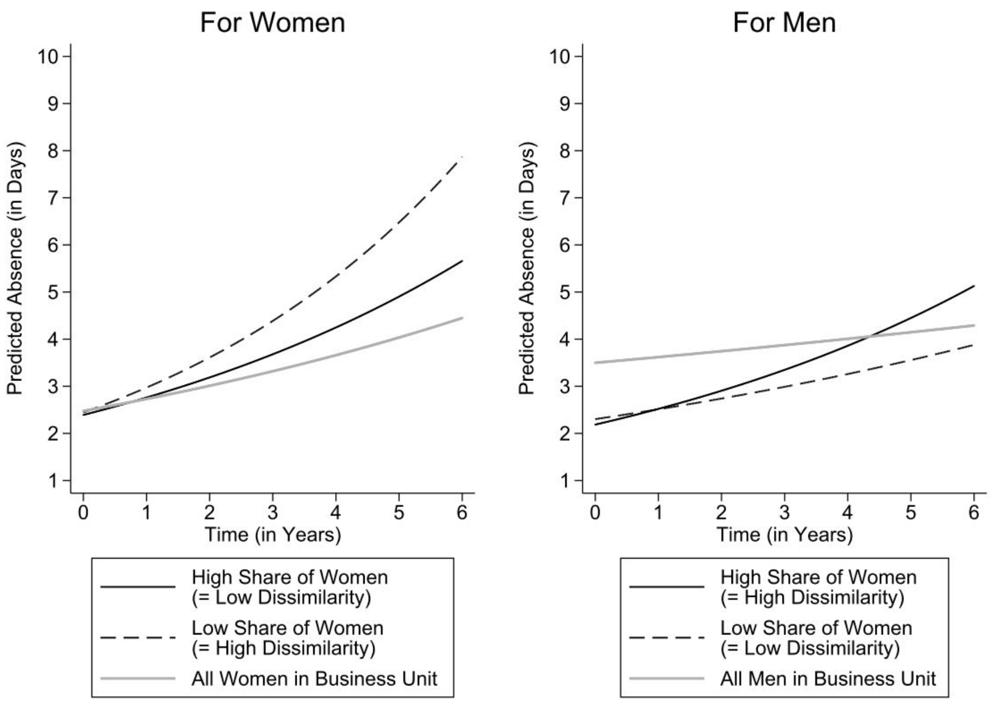
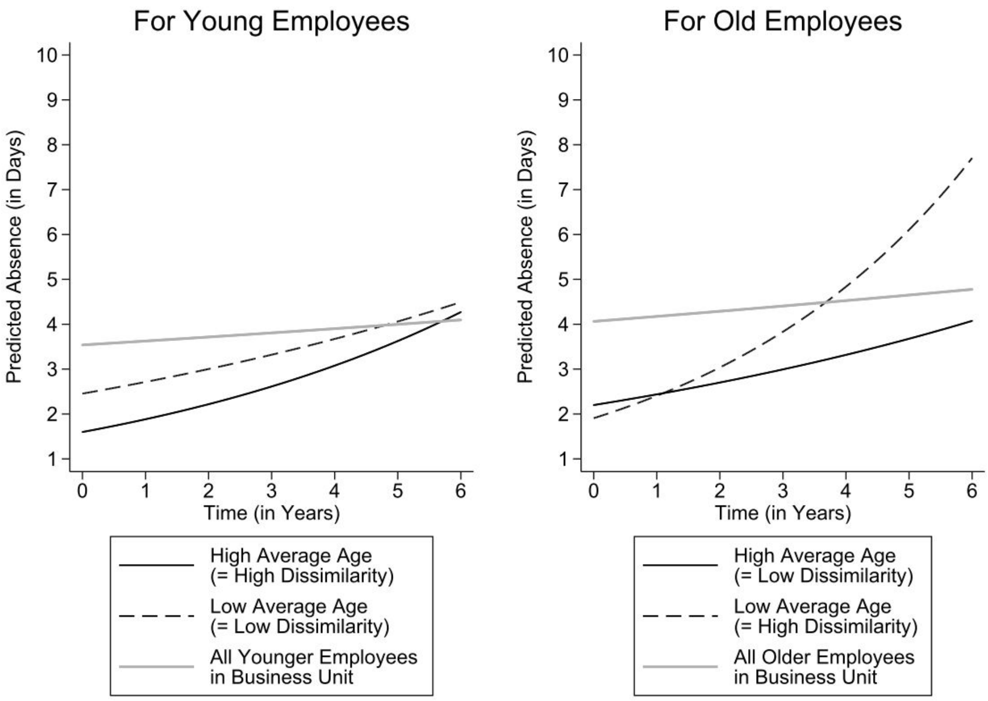


FIGURE 3 Predicted Conditional Absenteeism Growth Trajectory for Age Dissimilarity



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