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faculty of behavioural and social sciences

master's thesis

Built on Bonds: How Social Connections Shape Working Conditions of Central and Eastern European Migrants in The Netherlands over Time

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Are there deviations of the Master's thesis from the proposed plan?

☐No

☒Yes, please explain below the deviations

The original plan was to examine the effect of social connections on both working and housing conditions. It was decided to exclude housing conditions from the research and focus solely on working conditions, as the housing-related variables in the dataset were not suitable for the longitudinal research design. Additionally, the initial plan was to submit the thesis on February 6. However, due to the complexity of the data analysis, the deadline was postponed to March 6.

Abstract

Due to the enlargement of the European Union in 2004 and 2007, labor migration from Central and Eastern European countries to the Netherlands has increased in recent decades. These migrant workers are often employed in low-skilled jobs under poor working conditions. While the role of social capital in finding a job is well established, less is known about whether social capital can be leveraged to improve working conditions, despite the crucial role of working conditions in worker well-being. The present study examined the effect of social connections with both co-ethnic and native-born Dutch persons on a broad range of working conditions among Polish and Bulgarian labor migrants from 2013 to 2018, using the New Immigrant Survey - The Netherlands (NIS2NL). Bivariate Dual Change Score Modeling was employed to assess whether social contact predicts changes in working conditions over time. While both working conditions and social contact exhibited change over time, we found no evidence that social connections with either co-ethnic or native-born Dutch persons influence changes in working conditions. Our findings suggest that improving migrant working conditions requires institutional reform rather than relying only on informal mechanisms.

Introduction

The enlargements of the European Union in 2004 and 2007 led to a substantial increase in labor migrants from Central and Eastern European countries to Western European countries, including the Netherlands (Engbersen, 2013; Strockmeijer et al., 2019). Many of these labor migrants are drawn to sectors with a high demand for low-skilled, temporary, and flexible labor, such as food processing, distribution, and agriculture (Engbersen, 2013). Within these low-skilled jobs, Central and Eastern European migrants frequently experience poor working conditions, such as underpayment and extremely irregular work schedules (Friberg, 2012; McGauran et al., 2016; Siegmann & Williams, 2020; Szytniewski & van der Haar, 2022). It is well established that social contacts are crucial in accessing job opportunities (e.g. Boyd, 1989; Burt, 2004; Granovetter, 1974), and that connections to native-born individuals are particularly beneficial for migrants in their job search (Bilecen & Seibel, 2021; Kanas et al., 2011; Lancee, 2010, 2012; Lancee & Hartung, 2012). However, it is important to move beyond focusing solely on migrants' employment status and also consider the conditions of their jobs, as working conditions are a key factor in overall worker well-being (Barnay, 2016; Robone et al., 2011). Currently, little is known about how social ties with co-ethnic and native-born individuals enable migrants to move into jobs offering good working conditions. Working conditions are often defined as a multidimensional concept, including aspects related to the physical and social environment, work intensity, skill-utilization, job security, and adequate compensation (Burchell et al., 2014; Eurofound, 2021; Green, 2005).

To the best of our knowledge, only one study in Germany has investigated how jobs obtained through social contacts relate to working conditions other than wages or occupational prestige (Drever & Hoffmeister, 2008). Building on this knowledge gap, the present study conceptualizes working conditions as a multidimensional construct encompassing several dimensions of employment. Furthermore, this study approaches both working conditions and social relationships as dynamic processes. First, examining working conditions through a longitudinal lens is important because the employment strategies migrants adopt upon arrival to enter an unfamiliar labor market often differ from those they develop once they become more embedded in the local context (Ryan, 2022). Second, social networks evolve after migration: newcomers typically rely on a small number of co-ethnic ties, whereas those with longer residence tend to form more diverse networks also including native-born individuals (Bilecen & Lubbers, 2021; Lubbers et al., 2007; Ryan et al., 2008; Vacca et al., 2025). For instance, in the Dutch context, the duration of residence has been identified as a key predictor of informal contact frequency with native-born individuals, indicating that ties with Dutch citizens tend to develop gradually over time (Snel et al., 2006). Against this background, this study addresses the following overarching question:

How do social relationships influence the working conditions of Polish and Bulgarian labor migrants in the Netherlands over time?

Context: labor market flexibilization and the migration industry in the Netherlands

In 2024, the Netherlands was home to approximately 194,400 Polish and 60,500 Bulgarian migrants, making them the largest and third-largest groups of EU migrants in the country, respectively (CBS, 2024). However, these numbers likely underestimate the true size of these populations, as many labor migrants live and work in the Netherlands without official registration (Engbersen, 2013). Central and Eastern European labor migrants are disproportionately employed in temporary contracts and low-paid jobs compared to other migrant groups and native Dutch workers (Strockmeijer et al., 2019).

The rise in labor migration after the EU enlargements occurred within the broader framework of the EU's free-movement regulation. This principle of free mobility is a key element of labor market flexibilization and deregulation across the EU, intended to strengthen the EU economy and improve labor market efficiency (Jones, 2014). Due to this free mobility, labor migrants from the new EU member states no longer require a work permit in the Netherlands (European Parliament, 2025). This unrestricted mobility makes them particularly attractive to Dutch employers, who benefit from a readily available workforce willing to accept flexible working hours and lower wages than native-born workers (Ruhs & Anderson, 2012). Accordingly, employers in a range of sectors cited cost-reduction as the most important reason to hire labor migrants (Berkhout et al., 2014). However, the broader process of labor market flexibilization has been linked to a rise in precarious work in European countries, raising concerns about the position of labor migrants within these markets (Been & de Beer, 2022).

In the Netherlands, employment agencies play a key role in the recruitment of Central and Eastern European workers. Approximately 26% of these workers are employed through these intermediaries (Strockmeijer et al., 2017), while these estimations reach up to 60% for Polish labor migrants (Engbersen et al., 2011). Because these agencies profit from facilitating and managing migration, they are sometimes labelled as part of the migration industry (Jones, 2014). The years following the EU enlargements revealed that the employment agency sector frequently mistreated Central and Eastern European workers. According to the Dutch Labor Inspectorate, underpayment and exploitation of labor migrants are among the most common illegal practices in the employment agency sector (Nederlandse Arbeidsinspectie, 2016). Furthermore, many employment agencies recruit migrants by offering "package deals", including full-time jobs, accommodation, health insurance, and transport to work. While these offers may appear advantageous, they tightly link migrants' income, housing, transportation, and insurance to their employer, creating a strong dependency (Engbersen et al., 2011; Siegmann & Williams, 2020; Szytniewski & van der Haar, 2022; van Ostaijen et al., 2015). Due to the created dependency, migrants often have limited bargaining power and few alternatives when employment or housing arrangements break down. Hence, while the free movement of workers aims to strengthen the European economy, it also risks putting migrant workers in a vulnerable position in the Western European labor markets (Favell, 2008).

The Dutch government introduced measures aimed at enhancing migrant workers' working conditions, including the establishments of minimum standards for employment agencies (Ministerie van Sociale Zaken en Werkgelegenheid, 2024). While state intervention is essential in safeguarding migrant workers' rights (Been & de Beer, 2022), macro-level policies alone are insufficient to fully explain or influence migrants' lived realities. Migrant trajectories are also shaped by their own agency and decisions (Szytniewski & van der Haar, 2022), and their interpersonal relationships (Vacca et al., 2025). It seems that some migrants are able to secure jobs with better working conditions over time, while others remain in jobs with poor working conditions (Drever & Hoffmeister, 2008; Szytniewski & van der Haar, 2022). A possible explanation for these differing outcomes lies in the role of social relationships.

Theoretical framework

Social capital and the employment of migrants

Social relationships can be used to access and mobilize resources to achieve better outcomes in areas such as employment, which is known as the concept of social capital (Bourdieu, 1986; Lin, 2001). The role of social capital in finding a job has been studied extensively. This body of literature dates back to Granovetter (1974) who claimed that many employees found their job through their weak social contacts, and that these jobs have higher wages and better job characteristics than jobs found through other channels. Various studies support the claim that employment is often found through social connections among both migrants and non-migrants (Burt, 2004; Drever & Hoffmeister, 2008; Franzen & Hangartner, 2006; Granovetter, 1974; Kalter, 2011; Kalter & Kogan, 2014; Moreno Galbis et al., 2020), highlighting the value of social capital in the job search. Migrants may be even more dependent on their social networks when seeking for employment compared to non-migrants, mainly because of language barriers and limited familiarity with the formal job search procedures in the countries of destination (Drever & Hoffmeister, 2008; Kalter & Kogan, 2014). Empirical evidence from the Netherlands exemplifies this pattern: many Bulgarian labor migrants have obtained jobs through their social networks in the Netherlands (Engbersen et al., 2011), and Polish migrants frequently relied on relatives and friends already settled in the country to facilitate contact with employment agencies or potential employers (Szytniewski & van der Haar, 2022).

While social relationships can enhance access to the labor market, jobs obtained through these networks do not necessarily result in better job characteristics, such as higher earnings or occupational prestige (De Graaf & Flap, 1988; Franzen & Hangartner, 2006; Mouw, 2003). Among migrant populations, the evidence is similarly mixed. Several studies indicate that networks may channel migrants into employment with poor working conditions. For instance, first and second generation migrants in Germany who found their job through social networks were employed in more physically demanding and in worse environmental conditions than those who found their job through other channels (Drever & Hoffmeister, 2008). Furthermore, Central and Eastern European migrants who turned to friends or relatives for help in finding a job were more likely to be overqualified, meaning their skills and education surpassed their occupational level (Leschke & Weiss, 2020). The same was found among first-generation migrants from various backgrounds in Germany (Kracke & Klug, 2021). Similarly, Jewish migrants from the former Soviet Union who had many social contacts in Germany prior to migration were more likely to end up in low-status jobs compared to those with fewer contacts (Kalter & Kogan, 2014). Among Mexican migrants in Los Angeles, those who relied on social relationships in the job search ended up in jobs with lower wages (Joassart-Marcelli, 2014). However, social networks can also yield benefits: among Puerto Rican migrants in the United States, social capital was linked to higher earnings, but this effect was only observed for women (Aguilera, 2005). Similarly, two studies in the United States found that having more familial and friendship ties in the destination country increased Mexican migrants' earnings (Amuedo-Dorantes & Mundra, 2007; Munshi, 2003), contrasting the findings of Joassart-Marcelli's study (2014). Whether social relationships can aid in finding employment with good working conditions may depend on the composition of one's network and the resources embedded within it.

The role of bridging ties

Social capital can be mobilized to access the labor and housing market. However, can social connections also be leveraged to enhance migrants' working conditions over time? Drawing upon Putnam's (2000) theory of bonding and bridging ties, the answer to this question may depend on the composition of migrants' networks. Bonding ties refer to relationships with persons who share key similarities, while bridging ties connect individuals who differ in some important way. To access novel information about for instance the labor market, bridging across social circles is deemed to be important (Burt, 2004). The logic of bonding and bridging ties has been applied to ethnicity in the migration literature (e.g. Kanas et al., 2011; Lancee, 2010; Seibel & Van Tubergen, 2013). This literature suggests that ties with non-migrants may be particularly valuable in securing better jobs, as these connections offer access to broader networks and resources in the labor market. It is assumed here that the native-born population possess more and better information about the labor market, such as information about job openings and how to present oneself to employers. Several studies demonstrated the value of having ties to the native-born population for labor market integration

(Bilecen & Seibel, 2021; Kanas et al., 2011; Lancee, 2010, 2012; Lancee & Hartung, 2012). In contrast, information obtained through bonding ties may be more redundant and homogenous, and therefore, less useful in securing employment with good working conditions (Lancee, 2010). Consequently, co-ethnic networks can lock migrant workers into sectors and occupations that are located in poor segments of the labor market and that already have high shares of migrant labor (Friberg & Midtbøen, 2019; Joassart-Marcelli, 2014; Leschke & Weiss, 2020; Ryan et al., 2008).

While the role of social contacts in the job search is well established, few studies have explored how ties to native-born and co-ethnic persons relate to the conditions of employment. In Germany, Drever & Hoffmeister (2008) studied how jobs found through German or co-ethnic contacts related to the working conditions among first and second generation migrants. Working conditions included environmental conditions, the nature of the tasks performed, the degree of physical labor, and the risk of workplace accidents. They found that migrants who secured jobs through their social networks and lacked non-migrant friends were more likely to work in jobs involving routine tasks. Beyond this, no significant differences were observed between migrants with and without German friends (Drever & Hoffmeister, 2008). Furthermore, three longitudinal studies in Germany found that having inter-ethnic relationships with Germans was associated with higher occupational status over time among first-generation migrants (Kalter & Kogan, 2014; Lancee, 2012; Rüdel & Steinmann, 2024). Third, among non-EU migrants in the Netherlands, bridging ties with Dutch citizens were associated with higher income, while bonding ties with family showed no effect on earnings (Lancee, 2010). However, a study conducted in Germany among migrant men found that only those with higher levels of human capital, specifically in terms of language proficiency and education, derived monetary benefits from bridging ties with native-born persons (Lancee, 2016). This finding supports the idea that an individual's ability to leverage social relationships for goal attainment also depends on their social position (Lin, 2001).

Although social capital is generally conceptualized to support labor market integration, one's social relationships may not necessarily provide valuable information about job opportunities. The ability to mobilize social relationships for employment outcomes depends not only on the presence of ties, but also on the quality of the resources embedded within the network, and whether these resources actually flow through these connections (Granovetter, 1983; Ryan, 2011). While native-born individuals may possess more knowledge about the labor market, they may not necessarily share this information with their migrant contacts. For example, Mouw (2002) found limited inter-racial sharing of job information between Black and White communities in the United States. Information exchange is more likely to occur within strong ties, which is indicated by the level of trust, reciprocity, and intensity of the connection (Granovetter, 1983; Lin, 2001; Van der Gaag & Snijders, 2004). In this study, contact frequency with both co-ethnic and native-born individuals is used as a proxy for social capital, capturing one dimension of tie strength. We hypothesize:

Bridging ties with native-born Dutch persons are positively associated with improvements in the working conditions of Polish and Bulgarian labor migrants over time, whereas bonding ties with co-ethnic individuals are not associated with such improvements.

Methods

To answer the research question, this study uses the dataset "New Immigrant Survey – The Netherlands" (NIS2NL) (Lubbers et al., 2018). NIS2NL is a longitudinal panel study targeted at Polish, Turkish, Bulgarian, and Spanish migrants who recently moved to the Netherlands at the onset of the survey. The survey includes questions about demographic characteristics, migration history, living situation, education, employment, income, language skills, identification, social connections, and perceived discrimination. To answer our research question, only Polish and Bulgarian migrants were selected from the sample. Furthermore, students and those who were retired or long term sick or disabled were excluded. Prior to the start of the data analysis, our study was approved by the Ethics Committee of the Faculty of Behavioral and Social Sciences at the University of Groningen.

The survey was sent to the respondents' addresses, which were retrieved from the municipal registry. The municipal registry is a record of all individuals who are officially registered at an address in a Dutch municipality. In case of nonresponse, respondents were reminded of the survey two times by sending the questionnaire and a letter of reminder to their address. Respondents were surveyed in their native language and submitted their answers in writing, either digitally (CAWI) or on paper (PAPI). Respondents received a gift voucher of 10 Euros for their participation.

The data collection included four waves. The first wave was carried out in two batches in late 2013 and early 2014, the second wave in late 2014 and early 2015, the third wave in late 2016, and the fourth wave in early 2018. For the first wave, those registered in the Netherlands between June 2012 and January 2014 were approached. This resulted in a total of 18,626 approached migrants, of whom 6,941 were of Polish and 4,606 of Bulgarian origin. Of those contacted, 31.9% of the Poles and 23.1% of the Bulgarians responded successfully. For the following waves, only those who had taken part before, consented to further participation, and were still residing in the Netherlands were approached. The response rates were 55.0% for Poles and 57.4% for Bulgarians in wave 2, 65.4% for Poles and 64.2% for Bulgarians in wave 3, and 73.2% for Poles and 83.3% for Bulgarians in wave 4. The main reasons for attrition were refusal to participate in following waves and moving abroad. The percentage of Polish and Bulgarian who had moved abroad varied between 12.5% and 16.3% in wave 2, and 7.5% and 9.8% in wave 3, respectively.

Measures and descriptive variables

Working conditions

Working conditions will be modeled as a latent variable, comprised of items on job security, irregular hours, hazardous work, physically heavy work, and satisfaction with the earnings. The respondents answered the questions of these items with reference to their current job or, if not employed at time of the survey, the most recent job they had held in the Netherlands. Job security was measured through the question: *Are/were you employed on a permanent basis, on a temporary basis or on a casual basis.* Respondents were asked about irregular work hours with the following question: *During the past year, have you worked in the evenings, at night, or on the weekend?* (0= yes regularly, 1= yes, sometimes, 2= no, never). The questions concerning hazardous and physically demanding work were phrased as follows: *Do/did you do hazardous work?* (0= yes regularly, 1= yes, sometimes, 2= no, never), and *Do/did you do physically heavy work?* (0= yes, regularly, 1= yes sometimes, 2= no, never). Lastly, respondents were asked the question: *How satisfied were you with the earnings from your current/your last job?* (0= very dissatisfied – 4= very satisfied).

Contact frequency with co-ethnic and native-born individuals

The following questions were asked about respondents' social relationships with co-ethnic and native-born individuals: *How often do you spend time with [country of origin people] in your free time?* (0= never – 4= every day) and *How often do you spend time with Dutch people in your free time?* (0= never – 4= every day).

Descriptive variables

Several variables will only be used to describe the sample and will not be employed in the analytical model. These include country of birth (0= Poland, 1= Bulgaria), gender (0= male, 1= female), age, the highest level of education achieved in the country of origin (0= low education (less than primary – upper secondary), 3= high education (short- cycle tertiary – doctoral or equivalent)), and Dutch language skills. Language skills is a scale comprised of the following items: *How well would you say you understand Dutch when someone is speaking to you?* (0= not at all – 3= very well); *How well would you say you speak Dutch?* (0= not at all – 3= very well); *How well would you say you read Dutch?* (0= not at all – 3= very well); and *How well would you say you write Dutch?* (0= not at all – 3= very well). Furthermore, employment status of the sample will be described, where 1= working, 2= unemployed, 3= on maternity or paternity leave, and 4= something else. In addition, the types of jobs held by the respondents will be examined. This was measured by the item: *What is/was the name or title of your main job?* (1 = Professional and technical occupations such as: doctor, teacher; 2 = Higher administrator occupations such as: banker, executive; 3 = Clerical occupations such as: secretary, clerk, office manager; 4 = Sales occupations such as: sales manager, shop owner, shop assistant; 5 = Service occupations such as: restaurant owner, police officer; 6 = Skilled worker such as: foreman, motor mechanic, printer; 7 = Semi-skilled worker such as: bricklayer, bus driver, canner; 8 = Unskilled worker such as: laborer, porter, unskilled factory worker; 9 = Farm worker such as: farmer, farm laborer, tractor driver).

Analysis strategy

The present study fits a Bivariate Dual Change Score model to the data in order to assess whether this relatively novel approach provides a suitable framework for answering our research question. This longitudinal modeling strategy combines elements of Latent Change Score Modeling and Latent Growth Modeling, which are two complementary techniques within the Structural Equation Modeling framework to capture change over time (Kievit et al., 2018; McArdle, 2001). A Bivariate Dual Change Score Model allows for simultaneous estimation of local change (time-point to time-point deviations) and global change (change across all time points). We followed the tutorial by Kievit and colleagues (2018) to estimate the models.

Figure 1 depicts the analytical model. The observed variables are depicted by rectangles, the latent variables by circles, and the mean structure is captured by the triangle. Furthermore, the one-headed arrows represent regression coefficients, while the double-headed arrows represent covariances. Figure 1 shows that the latent variables of working conditions (w1- w4) have five indicator variables, whereas contact frequency (c1- c4) with native-born or co-ethnic persons has one indicator variable at each time point. The latent change scores are represented by Δc1 – Δc3 and Δw1 – Δw3. Each latent change score is defined by the subsequent time point, with its factor loading fixed to 1, and a self-feedback parameter from the preceding time point (red arrows). For instance, Δc1 is defined by c2 and a self-feedback parameter from c1. The self-feedback parameter indicates whether the magnitude of change depends on prior levels of contact frequency or working conditions. The yellow arrows depict the covariances between the latent change scores of working conditions and contact frequency. The green arrows represent the cross-domain coupling parameters, which depict the effect of contact frequency at a certain point in time on the change in working conditions. Together with the self-feedback parameters, the cross-domain coupling parameters represent local change dynamics.

The small latent change score models are connected by latent slopes and intercepts, which capture the global change in contact frequency and working conditions across all time points. The intercepts (Ic and Iw) represent the average scores of contact frequency and working conditions at wave 1, conditional on the other variables in the model. The slopes (Sc and Sw) depict the global increase or decrease across all waves. These latent slopes are defined by the latent change scores by specifying factor loadings (blue arrows). In our model, these factor loadings were fixed to 1, thereby assuming linear change. A more elaborated description of the overall model specification is given in the results.

The model in Figure 1 will be estimated for the two predictors: contact frequency with co-ethnic persons and contact frequency with native-born Dutch persons. For both predictors, we will estimate three models with slightly different structures. First, a no-change model will be estimated by fixing the self-feedback and the cross-domain coupling parameters to zero and by removing the slope. Thereby, the first model assumes there is no change in either working conditions or contact frequency over time. The second model will include the self-feedback parameters and slopes, but the cross-domain coupling parameter will be fixed to zero. This model will be compared to the no-change model, using a Chi-square difference test. If the second model demonstrates significantly better fit than the no-change model, this indicates that working conditions and contact frequency exhibit change over time. In the third model, the cross-domain coupling parameter will be estimated. The models including and excluding the cross-domain coupling parameter will be compared using a Chi-square difference test. If inclusion of the cross-domain coupling parameter significantly improves model fit, this means that contact frequency influences the change in working conditions. All analyses will be performed using *R*.

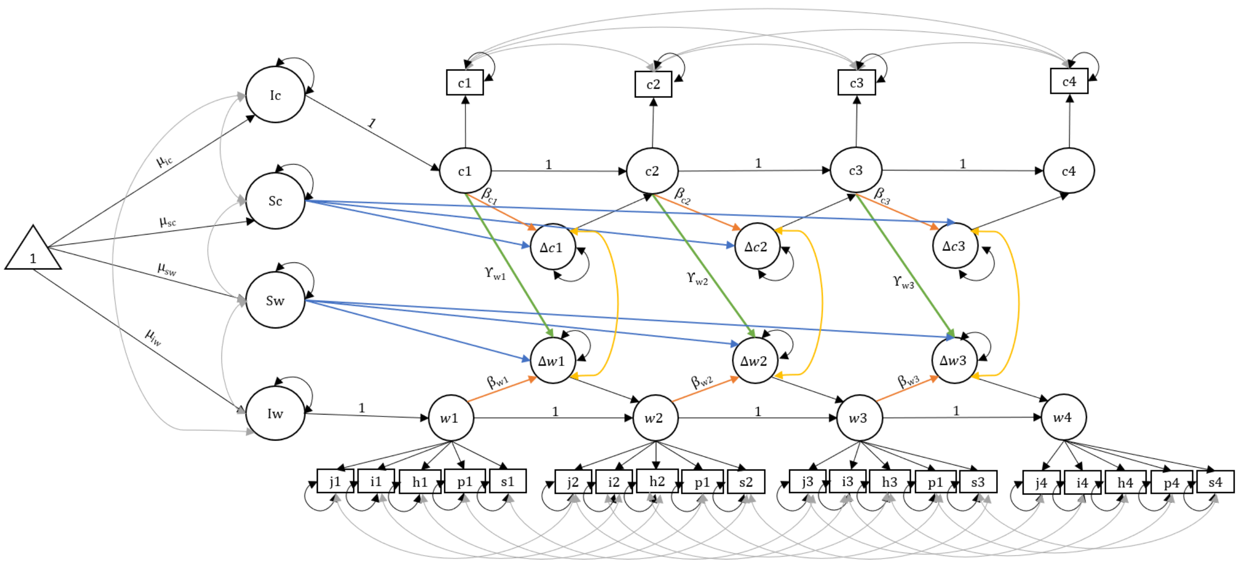

Figure 1: The statistical model including working conditions (*w)*, contact frequency (*c*), and the latent change scores of these variables (Δ).

Results

Complications

To estimate the models, we used Full Information Maximum Likelihood (FIML). This estimation method does not require the deletion or imputation of missing data, because FIML uses all available information to estimate model parameters by maximizing the likelihood of the observed data. FIML requires that the variables stem from a multivariate normal distribution. However, our variables are categorical and therefore not normally distributed. In the case of nonnormality, FIML can lead to inflation of model rejection rates and biased standard errors, thereby warranting caution in model evaluation and hypothesis testing (Enders, 2001). However, bias in parameter estimates is generally small. Despite violations of the normality assumption, we decided to use FIML, as the sample size was insufficient to employ (Diagonal) Weighted Least Squares estimation, an estimation method that is robust to conditions of nonnormality.

Substantial attrition occurred over time. As a result, only 205 respondents had complete data by wave 4, while 1,929 participants had missing data for at least one variable included in the analytical model. To assess potential differences between respondents with complete data and those with missing data for at least one variable, a missing data analysis was performed. The results, which are presented in Table 1 of the appendix, indicated that these two groups differed substantially for various variables. The most notable differences will be described below. First, Bulgarian migrants were underrepresented among the respondents with complete data: 16.10% of the complete respondents were of Bulgarian origin, compared to 23.59% among the respondents with missing data. Second, the findings indicate that women are more likely than men to drop out or to have missing data over time. This means that the longitudinal complete-case sample increasingly underrepresents female respondents relative to the original sample composition. Third, the respondents with complete data more often enjoyed high education (52.94%) than respondents with missing data (41.46%). In contrast, low- and medium educated respondents are more prevalent among the group with missing data. Furthermore, across waves, respondents with complete data were less likely to have casual contracts and more likely to have permanent contracts compared to respondents with missing data. By wave 4, 70.73% of complete cases have permanent contracts, compared to 49.59% among respondents with missing data. This indicates job security as a key predictor of panel retention. Lastly, in wave 3 and 4, respondents with complete data are more frequently in jobs that require regular or occasional hazardous work than respondents with missing data. Overall, the differences between respondents with complete and missing data indicate that the missing data are not missing at random. This indicates that the parameter estimations may be biased. However, FIML has been shown to yield less biased results than listwise or pairwise deletion methods when data are not missing at random (Enders, 2001; Muthén et al., 1987).

Univariate descriptive statistics

The descriptive statistics of the sample are given in Table 1. The variables included in this table will not be used in the final analyses but do provide valuable insight about the sample. Polish migrants are overrepresented in all waves, making up 77.13% of the sample. Across waves, the percentage of women is higher than the percentage of men. In addition, the sample is relatively young, with a mean age of 32 years at wave 1. Most respondents have completed higher education, namely 42.57%. Furthermore, 35.26% completed upper-secondary to non-tertiary education and 22.16% completed upper secondary education or lower. Mean language skills slightly increase over the years, with 0.93 at wave 1 to 1.49 at wave 4 on a scale from 0 to 3. However, a mean score of 1.48 indicates that the majority of respondents have limited Dutch language skills after several years of living in the Netherlands. Across waves, 69.98% to 79.45% of the respondents are working. The percentage of unemployed respondents drops from 18.81% to 9.66% over time. When we look at the occupation of the respondents, most (35.73% to 31.75%) indicate that they are unskilled workers, such as laborers, porters, or unskilled factory workers.

Table 1: Descriptive statistics of the sample (N= 2,134)

	Wave 1	Wave 2	Wave 3	Wave 4
Country of birth				
Poland	1,646 (77.13%)	1,646 (77.13%)	1,646 (77.13%)	1,646 (77.13%)
Bulgaria	488 (22.87%)	488 (22.87%)	488 (22.87%)	488 (22.87%)
Gender				
Male	936 (43.92%)	403 (41.04%)	225 (38.14%)	158 (37.00%)
Female	1,195 (56.08%)	579 (58.96%)	365 (61.86%)	269 (63.00%)
Unknown	3	1,152	1,544	1,707
Age (mean(SE))	32.00 (9.12)	34.13 (8.76)	35.22 (8.69)	37.69 (8.89)
Unknown	18	1,152	1,545	1,712
Education				
Low education (less than primary – upper secondary)	467 (22.16%)	467 (22.16%)	467 (22.16%)	467 (22.16%)
Medium education (upper secondary – non-tertiary)	743 (35.26%)	743 (35.26%)	743 (35.26%)	743 (35.26%)
High education (short- cycle tertiary – doctoral or equivalent)	897 (42.57%)	897 (42.57%)	897 (42.57%)	897 (42.57%)
Unknown	27	27	27	27
Mean language skills (SE) 0= poor Dutch language skills – 3= very good Dutch language skills	0.93 (0.63)	1.20 (0.64)	1.36 (0.66)	1.49 (0.67)
Unknown	31	1,160	1,552	1,710
Employment status				
Working	1,473 (69.98%)	715 (72.66%)	460 (79.45%)	324 (78.26%)
Unemployed	396 (18.81%)	151 (15.34%)	58 (10.01%)	40 (9.66%)
Looking after the home or children	150 (7.13%)	71 (7.22%)	47 (8.12%)	28 (6.76%)
On maternity or paternity leave	32 (1.52%)	16 (1.63%)	6.00 (1.04%)	11 (2.66%)
Other	54 (2.57%)	31 (3.15%)	8.00 (1.38%)	11 (2.66%)
Unknown	29	1,150	1,555	1,720
Job category				
Professional and technical occupations (e.g. doctor, teacher)		71 (10.23%)	45 (10.07%)	45 (14.29%)
Higher administrator occupations (e.g. banker, executive)		9 (1.30%)	6 (1.34%)	6 (1.90%)
Clerical occupations (e.g. secretary, clerk, office manager)		21 (3.03%)	14 (3.13%)	10 (3.17%)
Sales occupations (e.g. sales manager, shop owner, shop assistant)		15 (2.16%)	9 (2.01%)	7 (2.22%)
Service occupations (e.g. restaurant owner, police officer)		42 (6.05%)	22 (4.92%)	13 (4.13%)
Skilled worker (e.g. foreman, motor mechanic, printer)		74 (10.66%)	49 (10.96%)	40 (12.70%)
Semi-skilled worker (e.g. bricklayer, bus driver, cannery)		84 (12.10%)	50 (11.19%)	31 (9.84%)
Unskilled worker (e.g. laborer, porter, unskilled factory worker)		248 (35.73%)	151 (33.78%)	100 (31.75%)
Farm worker (e.g. farmer, farm laborer, tractor driver)		43 (6.20%)	33 (7.38%)	16 (5.08%)
I don’t know		87 (12.54%)	68 (15.21%)	47 (14.92%)
Unknown	2,134	1,440	1,687	1,819

The descriptive statistics of the variables included in the model are given in Table 2. The share of respondents in casual and temporary contracts decreases substantially over time from 8.68% to 2.45% and 62.44% to 34.66%, respectively. Conversely, the proportion holding permanent contracts rose from 28.88% in wave 1 to 62.88% in wave 4. The proportion of respondents working irregular hours remains relatively stable across waves, with about 50% reporting that they worked irregular hours occasionally. Similarly, the proportion of respondents engaged in hazardous work remains relatively stable across waves, with approximately 60% reporting that they never perform hazardous tasks. Furthermore, between 48.83% at wave 1 and 41.64% at wave 4 indicated that they performed physically demanding work occasionally. The percentage of persons who never perform physically heavy work increases from 23.38% at wave 1 to 31.61% at wave 4. Lastly, most respondents are somewhat satisfied with their earnings, namely around 50% across waves. However, the proportion of respondents who are very satisfied decreases from 20.31% to 13.11%, while the proportion who are somewhat dissatisfied increases from 7.81% to 14.33%.

The proportion of respondents who had daily contact with individuals from their country of origin declined over time, from 39.81% at wave 1 to 25.00% at wave 4. By wave 4, most respondents reported contact with co-ethnic individuals only a few times per month. The share of people who never interacted with Dutch individuals in their free time decreased slightly from 17.44% at wave 1 to 12.77% at wave 4. At the same time, the percentage of those who interact daily or a few times a week with native-born Dutch persons declines over time. This means that there is a trend toward more moderate but regular contact.

Table 2: Descriptive statistics of variables included in the end model (N=2,134)

	Wave 1	Wave 2	Wave 3	Wave 4
Job security				
Casual contract	152 (8.68%)	43 (6.18%)	12 (2.64%)	8 (2.45%)
Temporary contract	1,094 (62.44%)	386 (55.46%)	215 (47.36%)	113 (34.66%)
Permanent contract	506 (28.88%)	267 (38.36%)	227 (50.00%)	205 (62.88%)
Unknown	382	1,438	1,680	1,808
Irregular hours				
Yes, regularly	410 (22.79%)	177 (24.82%)	119 (25.87%)	85 (25.84%)
Yes, sometimes	905 (50.31%)	359 (50.35%)	210 (45.65%)	155 (47.11%)
No, never	484 (26.90%)	177 (24.82%)	131 (28.48%)	89 (27.05%)
Unknown	335	1,421	1,674	1,805
Hazardous work				
Yes, regularly	116 (6.47%)	40 (5.59%)	45 (9.78%)	31 (9.39%)
Yes, sometimes	586 (32.68%)	233 (32.59%)	148 (32.17%)	108 (32.73%)
No, never	1,091 (60.85%)	442 (61.82%)	267 (58.04%)	191 (57.88%)
Unknown	341	1,419	1,674	1,804
Physical work				
Yes, regularly	498 (27.79%)	180 (25.17%)	112 (24.35%)	88 (26.75%)
Yes, sometimes	875 (48.83%)	330 (46.15%)	226 (49.13%)	137 (41.64%)
No, never	419 (23.38%)	205 (28.67%)	122 (26.52%)	104 (31.61%)
Unknown	342	1,419	1,674	1,805
Satisfaction with earnings				
Very dissatisfied	76 (4.30%)	27 (3.78%)	14 (3.08%)	13 (3.96%)
Somewhat dissatisfied	138 (7.81%)	55 (7.69%)	59 (12.97%)	47 (14.33%)
Neither satisfied nor dissatisfied	320 (18.10%)	127 (17.76%)	77 (16.92%)	65 (19.82%)
Somewhat satisfied	875 (49.49%)	348 (48.67%)	245 (53.85%)	160 (48.78%)
Very satisfied	359 (20.31%)	158 (22.10%)	60 (13.19%)	43 (13.11%)

Unknown	366	1,419	1,679	1,806
Contact frequency with co-ethnics				
Never	106 (4.99%)	44 (4.50%)	26 (4.44%)	20 (4.72%)
Less often (than several times a year)	169 (7.95%)	90 (9.21%)	44 (7.52%)	32 (7.55%)
Several times a year	151 (7.11%)	113 (11.57%)	74 (12.65%)	66 (15.57%)
A few times a month	476 (22.40%)	245 (25.08%)	178 (30.43%)	131 (30.90%)
Several times a week	377 (17.74%)	185 (18.94%)	100 (17.09%)	69 (16.27%)
Everyday	846 (39.81%)	300 (30.71%)	163 (27.86%)	106 (25.00%)
Unknown	9	1,157	1,549	1,710
Contact frequency with Dutch				
Never	370 (17.44%)	145 (14.81%)	79 (13.53%)	54 (12.77%)
Less often (than several times a year)	405 (19.09%)	204 (20.84%)	98 (16.78%)	83 (19.62%)
Several times a year	237 (11.17%)	137 (13.99%)	91 (15.58%)	79 (18.68%)
A few times a month	382 (18.00%)	177 (18.08%)	121 (20.72%)	87 (20.57%)
Several times a week	352 (16.59%)	154 (15.73%)	101 (17.29%)	56 (13.24%)
Everyday	376 (17.72%)	162 (16.55%)	94 (16.10%)	64 (15.13%)
Unknown	12	1,155	1,550	1,711

Bivariate Dual Change Score Models

Model specification

A visualization of the analytical model is given in Figure 1. The latent working conditions variable has five indicator variables: job security, irregular hours, hazardous work, physically heavy work, and satisfaction with earnings. For identification purposes, the factor loading of job security was fixed to 1 for each wave. All other factor loadings were freely estimated, as this specification resulted in better model fit compared to imposing measurement invariance. Furthermore, the indicator variables were constrained to have equal variances over time because their variances remained relatively stable across waves. Contact frequency was modeled as a single-indicator latent variable, thereby assuming perfect measurement. The self-feedback parameters (represented by the red arrows) were fixed to zero and the latent slopes were removed in the first model, representing the no-change model. The self-feedback parameters were fixed to have the same value over time in the second and third models, because freely estimating these parameters did not yield a significantly better model fit. The cross-domain coupling parameters (represented by the green arrows) were fixed to zero in the first and second model and estimated with a constant value over time in the final model. The covariances between change scores (represented by the yellow arrows) and the variances of the change scores were freely estimated. The same specification applies to the covariances and variances of the other latent variables, including the latent intercepts and slopes. Lastly, the means of the growth factors were freely estimated.

No-change vs. no cross-domain coupling models

For both contact frequency with co-ethnic and native-born persons, the second model in which the cross-domain coupling parameters were fixed to zero performed significantly better than the no-change model. For the model including co-ethnic contact frequency, a chi-square difference test yielded a difference in degrees of freedom of 11 and a chi-square difference of 176.01 ($p < 0.01$). For contact frequency with native-born Dutch persons, the difference in degrees of freedom was 11 and the chi-square difference was 181.22 ($p< 0.01$). This indicates that both working conditions and contact frequency with co-ethnic and native-born Dutch persons change over time.

No cross-domain coupling vs. cross-domain coupling models

The results of the models including and excluding the cross-domain coupling parameter for both Dutch and co-ethnic contacts are included in Table 3. Since the model incorporating cross-domain coupling parameters represents the most complete specification, the interpretation below focuses only on this model for both contact frequency with co-ethnic and native-born persons. At the end of each model interpretation, the cross-domain coupling model will be compared to no cross-domain coupling model in terms of model fit.

Cross-domain coupling model including co-ethnic contact frequency

None of the standardized factor loadings are close to one, indicating that the indicators are not strongly related to the latent variable of working conditions. At wave 1, the indicators irregular hours and physical work have the lowest communalities ($0.25^2= 0.06$), while satisfaction with earnings has the largest communality ($0.46^2= 0.21$). This means that approximately 6% of the variances of irregular hours and physical work, and 21% of the variance of job security is explained by working conditions.

The intercept estimate of working conditions is 1.20, which represents the expected mean levels of working conditions at wave 1, conditional on the other variables. The associated variance is small, namely 0.04. This means that there is little intra-individual variation in the mean at wave 1. The intercept of co-ethnic contact frequency is 3.60. The associated variance of 1.32 shows that there is a high degree of variability between respondents in how much time they spent with co-ethnic peers in their free time at wave 1. All covariances between the growth factors are negligible, except for the covariance between the intercept and slope of co-ethnic contact frequency. The covariance of 0.63 shows that higher initial levels of co-ethnic contact are associated with more change in contact frequency.

The table includes several parameters which are related to the expected change. First, the Dual Change Score equation of co-ethnic contact frequency can be written as (McArdle, 2001):

$$E\{\Delta \text{contact freq. } [t]_n\}= \alpha c * \mu c + \beta c * E\{\text{contact freq. } [t\text{-}1]_n\}$$

In this equation, αc represents the loading of the latent slope on the change scores and is fixed to 1. This parameter is represented by the blue arrows in Figure 1. The parameter μc is the mean of the latent slope factor, capturing the average change in co-ethnic contact frequency. βc is the self-feedback parameter, represented by the red arrows in Figure 1. E{contact freq. [t-1]n} reflects that change in contact frequency depends on the individual's prior level of social contact. For instance, for a person with an initial level of co-ethnic contact frequency of 3.60, the change score from wave 1 to wave 2 is as follows:

$E\{\Delta \text{ contact freq. } 1\} = 2.04 - 0.61 * 3.60 = - 0.16$

Due to the cross-domain coupling parameter, the dynamic structural equation of working conditions looks slightly different (McArdle, 2001):

$E\{\Delta\text{working con. } [t]_n\} = \alpha w * \mu w + \beta w * E\{\text{working con. } [t\text{-}1]_n\} + \Upsilon w * E\{\text{contact freq. } [t\text{-}1]_n\}$

Where Υw represents the cross-domain coupling effect, indicating how prior contact frequency predicts subsequent change in working conditions. This means that for each person, the expected change in working conditions from one wave to the next depends on a constant tendency to change, how good or bad their working conditions previously were, and how much time they spent with co-ethnic contacts previously.

For a person with initial scores of 1.20 on working conditions and 3.60 on co-ethnic contact frequency, this results in the following predicted change score between wave 1 and 2:

$E\{\Delta \text{ working con. } 1\} = 0.13 + 0.03 * 1.20 - 0.01 * 3.60 = 0.13$

The positive slope shows that the mean score grows additively by 0.13 from one wave to the next. The positive self-feedback coefficient of 0.03 indicates that higher initial levels of working conditions are associated with slightly greater change over time. However, the effect is very small. The cross-domain coupling effect is −0.01, meaning that higher prior levels of co-ethnic contact frequency lead to smaller changes in working conditions. Again, the effect is very small. This is also shown by the covariances between the latent change scores of working conditions and co-ethnic contact frequency, which are close to zero.

The cross-domain coupling model yields a significant chi-square value of 2044.14, a CFI of 0.51, and a SRMR of 0.14. These fit indices suggest inadequate model fit, given that acceptable fit is typically indicated by CFI values above 0.95 and SRMR values below 0.04. However, the 95% confidence interval of the RMSEA, ranging between 0.05 and 0.06, falls below the 0.10 threshold, pointing at acceptable model fit.

We assessed whether the cross-domain coupling parameter added significantly to the model fit by comparing the models with and without this parameter using a Chi-square test. The difference in chi-square values was 0.06 with a difference of 1 degree of freedom ($p = 0.80$). This means that the models do not significantly differ in model fit, indicating that the cross-domain coupling parameters from co-ethnic contact frequency to change in working conditions do not improve the model. This is in line with our hypothesis, stating that co-ethnic contact is not associated with improvements in working conditions over time.

Cross-domain coupling model including contact frequency with Dutch persons

The factor loadings are similar to the model including co-ethnic contact frequency. Again, working conditions explains the most variance in satisfaction with earnings (21.16%) and the least in irregular hours and physically demanding work (6.25%) at wave 1. These percentages point at a weak relationship between the indicators and the latent variable.

At wave 1, the expected mean level of working conditions is 1.20 and the mean level of Dutch contact frequency is 2.50. Their variances are 0.04 and 1.83, respectively. This shows that respondents differ more in their initial level of Dutch contact frequency compared to their initial level of working conditions. All covariances between the growth factors are very small, except for the covariance between the intercept and slope of contact frequency with native-born Dutch persons. The positive covariance of 0.43 shows that higher initial levels of contact is associated with more change in contact frequency over time.

To assess the change in contact frequency with Dutch persons over time, the following equation can be written:

$E\{\Delta \text{ contact freq. } [t]_n\} = 0.91 - 0.36 * E\{\text{contact freq. } [t]_n\}$

This equation shows that for any positive initial value, the expected mean will always increase additively by 0.91 and decrease proportionally over time. The magnitude of the decrease depends on the previous levels of working conditions.

The equation for change in working conditions is written below:

$E\{\Delta \text{ working con. } [t]_n\} = -0.10 + 0.09 * E\{\text{working con. } [t]_n\} + 0.04 * E\{\text{contact freq. } [t]_n\}$

The equation indicates that the expected mean will always decrease by 0.10 from one wave to the next. The positive self-feedback parameter of 0.09 shows that better initial working conditions result in more change over time. The cross-domain coupling score of 0.04 is positive, but very small. It shows that higher levels of contact with native-born Dutch persons are associated with slight improvements in working conditions over time. However, the covariances of the latent change scores of working conditions and contact frequency with Dutch persons are close to zero, indicating that the changes in these two latent variables are practically unrelated.

The model has a significant chi-square value of 2028.72, a CFI of 0.50, and a SRMR of 0.14. These fit indices suggest inadequate model fit. However, the 95% confidence interval of the RMSEA, ranging between 0.05 and 0.06, suggests acceptable model fit.

Again, the model excluding the cross-domain coupling parameter was compared to the model including this parameter. This test yielded a difference in Chi-square values of 1.00 with a difference of 1 degree of freedom ($p = 0.32$). This suggests that the inclusion of the cross-domain coupling parameter does not add to the model fit. This contradicts our hypothesis that contact with native-born Dutch individuals results in improved working conditions over time.

Table 3: Parameter & fit indices for the analytical models (N=2132)

Parameter & fit indices	Model no cross-domain coupling Co-ethnic contacts	Dutch contacts	Model cross-domain coupling Co-ethnic contacts	Dutch contacts
Factor loadings (Std. All)				
Wave 1				
Job security	1.00 (0.35)	1.00 (0.35)	1.00 (0.35)	1.00 (0.35)
Irregular hours	0.88** (0.25)	0.87** (0.25)	0.88** (0.25)	0.87** (0.25)
Hazardous work	1.29** (0.43)	1.29** (0.43)	1.29** (0.43)	1.29** (0.43)
Physical work	0.82** (0.25)	0.82** (0.25)	0.82** (0.25)	0.82** (0.25)
Satisfaction earnings	2.29** (0.46)	2.29** (0.46)	2.29** (0.46)	2.29** (0.46)
Wave 2				
Job security	1.00 (0.39)	1.00 (0.39)	1.00 (0.39)	1.00 (0.39)
Irregular hours	0.76** (0.25)	0.76** (0.25)	0.76** (0.25)	0.76** (0.25)
Hazardous work	1.18** (0.45)	1.18** (0.45)	1.18** (0.45)	1.18** (0.45)
Physical work	0.81** (0.28)	0.81** (0.28)	0.81** (0.28)	0.81** (0.28)
Satisfaction earnings	2.08** (0.47)	2.09** (0.48)	2.08** (0.48)	2.09** (0.48)
Wave 3				
Job security	1.00** (0.44)	1.00** (0.44)	1.00** (0.44)	1.00** (0.44)
Irregular hours	0.71** (0.27)	0.71** (0.27)	0.71** (0.27)	0.71** (0.27)
Hazardous work	1.03** (0.45)	1.04** (0.45)	1.03** (0.45)	1.04** (0.45)
Physical work	0.73** (0.29)	0.73** (0.29)	0.73** (0.29)	0.73** (0.29)
Satisfaction earnings	1.80** (0.47)	1.81** (0.47)	1.80** (0.47)	1.81** (0.47)
Wave 4				
Job security	1.00 (0.49)	1.00 (0.48)	1.00 (0.49)	1.00 (0.49)
Irregular hours	0.64** (0.28)	0.64** (0.28)	0.64** (0.28)	0.64** (0.28)
Hazardous work	0.95**(0.46)	0.94**(0.46)	0.95**(0.46)	0.94**(0.46)
Physical work	0.69**(0.31)	0.69**(0.31)	0.69**(0.31)	0.69**(0.31)
Satisfaction earnings	1.59** (0.47)	1.59** (0.47)	1.59** (0.47)	1.59** (0.47)
Growth factors				
Intercept work	1.20**	1.20**	1.20**	1.20**
Intercept contact frequency	3.60**	2.50**	3.60**	2.50**
Slope work	0.06	0.01	0.13	-0.10
Slope contact freq.	2.05*	0.92	2.04*	0.91
Self-feedback				
Working conditions	0.04	0.09	0.03	0.09
Contact frequency	-0.61*	-0.37	-0.61*	-0.36
Cross-domain coupling	N.A.	N.A.	-0.01	0.04
Variances				
Intercept work	0.04**	0.04**	0.04**	0.04**
Intercept contact frequency	1.32**	1.83**	1.32**	1.83**
Slope work	0.00	0.00	0.00	0.00
Slope contact freq.	0.42	0.24	0.42	0.24
Δ*w*ork 1	0.00	0.00	0.00	0.00
Δ*w*ork 2	0.00	0.00	0.00	0.00
Δ*w*ork 3	0.00	0.00	0.00	0.00
Δcontact freq. 1	0.14	0.17	0.14	0.17
Δcontact freq. 2	0.02	0.07	0.02	0.07
Δcontact freq. 3	0.00	0.03	0.00	0.03
Residual variances				
Job security	0.30**	0.31**	0.30**	0.31**
Irregular hours	0.47**	0.47**	0.47**	0.47**
Hazardous work	0.31**	0.31**	0.31**	0.31**
Physical work	0.43**	0.43**	0.43**	0.43**
Satisfaction earnings	0.83**	0.82**	0.83**	0.82**
Contact frequency	0.94**	1.27**	0.94**	1.27**
Covariances				
Intercept work & slope work	0.00	0.00	0.00	0.00
Intercept contact freq. & slope contact freq.	0.63	0.43	0.63	0.43
Intercept work & intercept contact freq.	-0.06**	0.05**	-0.06**	0.05**

Intercept work & slope contact freq.	-0.03	0.02	-0.03	0.03
Slope work & slope contact freq.	-0.02	0.00	-0.01	-0.02
Slope work & intercept contact freq.	-0.01	0.01	0.00	-0.06
Δ*w*ork 1 & Δcontact freq. 1	-0.01	0.00	-0.00	-0.01
Δ*w*ork 2 & Δcontact freq. 2	-0.00	0.00	-0.00	0.00
Δ*w*ork 3 & Δcontact freq. 3	-0.00	0.00	-0.00	0.00
Parameters	60	60	63	63
Degrees of freedom	286	286	285	285
Chi^2	2044.17**	2029.21**	2044.14**	2028.72**
RMSEA 90% confidence interval	(0.05, 0.06)	(0.05, 0.06)	(0.05, 0.06)	(0.05, 0.06)
CFI	0.51	0.50	0.51	0.50
SRMR	0.14	0.14	0.14	0.14

* indicates p < .05. ** indicates p < .01.

Discussion

This study examined how the working conditions of Polish and Bulgarian labor migrants in the Netherlands are influenced by contact frequency with co-ethnic and native-born Dutch persons. While both working conditions and contact frequency exhibited change over time, we found no evidence that contact frequency with either co-ethnic or native-born Dutch persons influences changes in working conditions.

While previous research showed that social ties play an important role in finding employment (Burt, 2004; Drever & Hoffmeister, 2008; Franzen & Hangartner, 2006; Granovetter, 1974; Kalter, 2011; Kalter & Kogan, 2014; Moreno Galbis et al., 2020), our findings suggest that migrants' social connections are less influential in securing employment with better working conditions over time. This contradicts prior longitudinal studies conducted in Germany (Kalter & Kogan, 2014; Lancee, 2012; Lancee, 2016; Rüdel & Steinmann, 2024), and a cross-sectional study conducted in The Netherlands (Lancee, 2010), which found that having bridging ties with native-born persons was associated with better working conditions among migrants. However, these studies only considered occupational prestige and salary, whereas the present study considers a broad range of working conditions. Our findings are consistent with those of Drever and Hoffmeister (2008), who likewise examined a broad range of working conditions using longitudinal data and found that the ethnic composition of social networks had little effect on working conditions among migrants in Germany.

One possible explanation for the limited impact of social connections on working conditions are structural constraints, such as labor market segmentation and the dependence of labor migrants on employment agencies (Engbersen et al., 2011; Felbo-Kolding et al., 2019; Siegmann & Williams, 2020; Szytniewski & van der Haar, 2022; van Ostaijen et al., 2015), that may limit upward mobility among migrant workers despite social ties with the native-born population. Second, the present study did not control for human capital, while previous research suggests that language proficiency and educational attainment are important predictors of whether migrants are able to benefit from ties with native-born persons. Those with higher levels of human capital were able to secure better working conditions through their native-born contacts, while those with lower levels of human capital were not (Lancee, 2016). Future research may want to control for educational attainment and language proficiency to assess whether the impact of social connections depends on human capital.

This study has two main contributions to the literature. First, the present study examined a broad range of working conditions, including job security, irregular working hours, the performance of hazardous and physically heavy work, and satisfaction with earnings. Previous research has typically focused on the role of social networks in either labor market entry or outcomes such as occupational prestige, salary, or overqualification. It is important to examine working conditions more broadly, as these conditions play a key role in overall worker well-being (Barnay, 2016; Robone et al., 2011). Second, the present study adds to the literature by employing a dynamic perspective on the connection between working conditions and social relationships, using Bivariate Dual Change Score modeling. Previous research highlighted the dynamic nature of migrant networks, underscoring the importance of examining them longitudinally (Bilecen & Lubbers, 2021; Lubbers et al., 2007; Ryan et al., 2008; Vacca et al., 2025).

This study is not without limitations. First, we used contact frequency with co-ethnic and native-born Dutch persons as a measure of social capital. However, contact frequency may not capture the resource-generating aspects of social capital, such as gaining access to labor market information. For example, a Polish migrant can spend time with a Dutch friend frequently without discussing anything related to employment. This means that the presence of ties is not enough to leverage one's social relationships for employment outcomes. The ability to do so also depends on the quality of resources embedded within the relationships and whether these resources are actually shared (Granovetter, 1983; Ryan, 2011). Future studies can use a more direct measure of social capital to assess the impact of social ties on working conditions. Furthermore, future research could conduct qualitative interviews to expand our understanding of the content and quality of co-ethnic and inter-ethnic ties among migrants. Second, non-EU labor migrants were not included in the present study. However, non-EU migrants often require a visa an work permit to access the Dutch labor market, which creates a markedly different context for this group (De Lange et al., 2019). Future studies would benefit from investigating whether the relationship between working conditions and social connections differs for non-EU migrant populations. Lastly, due to a high proportion of missing data, the sample was insufficient to employ (Diagonal) Weighted Least Square estimation. Therefore, we used Full Information Maximum Likelihood estimation, despite non-normally distributed variables. While bias in parameter estimation is generally small, FIML can lead to inflation of model rejection rates and biased standard errors. Future research could explore the use of missing data imputation techniques to address issues arising from non-normally distributed variables in Bivariate Dual Change Score modeling.

Conclusion

Despite limitations, the present study contributed to the literature by examining the effect of social connections of migrants with co-ethnic and native-born persons on a broad range of working conditions longitudinally. While social connections may facilitate labor market entry, this study found that they are less influential in securing employment with better working conditions over time. This means that improving migrant working conditions requires institutional reform rather than relying only on informal mechanisms.

Bibliography

Aguilera, M. B. (2005). The Impact of Social Capital on the Earnings of Puerto Rican Migrants. *The Sociological Quarterly*, *46*(4), 569–592. https://doi.org/10.1111/j.1533-8525.2005.00027.x

Amuedo-Dorantes, C., & Mundra, K. (2007). Social networks and their impact on the earnings of Mexican Migrants. *Demography*, *44*(4), 849–863. https://doi.org/10.1353/dem.2007.0039

Barnay, T. (2016). Health, work and working conditions: A review of the European economic literature. *The European Journal of Health Economics*, *17*(6), 693–709. https://doi.org/10.1007/s10198-015-0715-8

Been, W., & de Beer, P. (2022). Combatting exploitation of migrant temporary agency workers through sectoral self-regulation in the UK and the Netherlands. *European Journal of Industrial Relations*, *28*(2), 175–191. https://doi.org/10.1177/09596801211052532

Berkhout, E., Bisschop, P., & Volkerink, M. (2014). *Grensoverschrijdend aanbod van personeel: Verschuivingen in nationaliteit en contractvormen op de Nederlandse arbeidsmarkt 2001-2011*. SEO Economisch Onderzoek. https://dare.uva.nl/search?identifier=ad06d1b5-35ba-4ba3-bf4f-0990aa5c28f0

Bilecen, B., & Lubbers, M. J. (2021). The networked character of migration and transnationalism. *Global Networks*, *21*(4), 837–852. https://doi.org/10.1111/glob.12317

Bilecen, B., & Seibel, V. (2021). Network explanations of the gender gap in migrants’ employment patterns: Use of online and offline networks in the Netherlands. *Journal of Family Research*, *33*(2), 541–565. https://doi.org/10.20377/jfr-484

Bourdieu, P. (1986). The forms of capital. In J. G. Richardson (Ed.), *Handbook of Theory and Research for the Sociology of Education* (pp. 241–261). Greenwood Press.

Boyd, M. (1989). Family and Personal Networks in International Migration: Recent Developments and New Agendas. *The International Migration Review*, *23*(3), 638–670. https://doi.org/10.2307/2546433

Burchell, B., Sehnbruch, K., Piasna, A., & Agloni, N. (2014). The quality of employment and decent work: definitions, methodologies, and ongoing debates. *Cambridge journal of economics, 38*(2), 459-477. https://doi.org/10.1093/cje/bet067

Burt, R. S. (2004). Structural Holes and Good Ideas. *American Journal of Sociology*, *110*(2), 349–399. https://doi.org/10.1086/421787

CBS. (2024, June 4). *Ruim 745 duizend mensen met andere EU-nationaliteit in Nederland*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/nieuws/2024/23/ruim-745-duizend-mensen-met-andere-eu-nationaliteit-in-nederland

De Graaf, N. D., & Flap, H. D. (1988). "With a Little Help from My Friends": Social Resources as an Explanation of Occupational Status and Income in West Germany, The Netherlands, and the United States*. *Social Forces*, *67*(2), 452–472. https://doi.org/10.1093/sf/67.2.452

De Lange, T., Oomes, N., Gons, N., & Spanikova, V. (2019). *Labour Migration and Labour Market Integration of Migrants in the Netherlands: Barriers and Opportunities* (Nr. 2019–24). SEO Amsterdam Economics. https://www.seo.nl/wp-content/uploads/2019/01/Annex_D_Barriers_to_Migration_and_Integration.pdf

Drever, A. I., & Hoffmeister, O. (2008). Immigrants and social networks in a job-scarce environment: The case of Germany. *International Migration Review*, *42*(2), 425–448. https://doi.org/10.1111/j.1747-7379.2008.00130.x

Enders, C. K. (2001). The impact of nonnormality on full information maximum-likelihood estimation for structural equation models with missing data. *Psychological Methods, 6*(4), 352–370. https://doi.org/10.1037/1082-989x.6.4.352

Engbersen, G. (2013). Labour migration from Central and Eastern Europe and the implications for integration policy. In J. W. Holtslag, M. Kremer, & E. Schrijvers (Eds.), *Making Migration Work: The future of labour migration in the European Union.* (pp. 105–116). https://doi.org/10.26530/oapen_448322

Eurofound. (2021). *Working conditions and sustainable work: An analysis using the job quality framework* (No. 190109; pp. 1–80). https://doi.org/doi:10.2806/938302

Engbersen, G., Ilies, M., Leerkes, A., Snel, E., & van der Meij, R. (2011). *Arbeidsmigratie in vieren*. Erasmus University Rotterdam. https://repub.eur.nl/pub/33030

European Parliament. (2025, March 31). *Free movement of workers*. https://www.europarl.europa.eu/factsheets/en/sheet/41/free-movement-of-workers

Favell, A. (2008). *Eurostars and Eurocities: Towards a sociology of free moving professionals in Western Europe*. Blackwell Publishing. https://doi.org/10.1002/9780470712818

Felbo-Kolding, J., Leschke, J., & F. Spreckelsen, T. (2019). A division of labour? Labour market segmentation by region of origin: the case of intra-EU migrants in the UK, Germany and Denmark. *Journal of Ethnic and Migration Studies, 45*(15), 2820–2843. https://doi.org/10.1080/1369183X.2018.1518709

Franzen, A., & Hangartner, D. (2006). Social Networks and Labour Market Outcomes: The Non-Monetary Benefits of Social Capital. *European Sociological Review*, *22*(4), 353–368. https://doi.org/10.1093/esr/jcl001

Friberg, J. H. (2012). The Stages of Migration. From Going Abroad to Settling Down: Post-Accession Polish Migrant Workers in Norway. *Journal of Ethnic and Migration Studies*, *38*(10), 1589–1605. https://doi.org/10.1080/1369183X.2012.711055

Friberg, J. H., & Midtbøen, A. H. (2019). The Making of Immigrant Niches in an Affluent Welfare State. *International Migration Review*, *53*(2), 322–345. https://doi.org/10.1177/0197918318765168

Granovetter, M. (1974). *Getting a Job: A Study of Contacts and Careers*. The University of Chicago Press.

Granovetter, M. (1983). The Strength of Weak Ties: A Network Theory Revisited. *Sociological Theory*, *1*, 201. https://doi.org/10.2307/202051

Green, F. (2005). *Demanding Work*. Princeton University Press. https://doi.org/10.1515/9781400849437

Joassart-Marcelli, P. (2014). Gender, social network geographies, and low-wage employment among recent Mexican immigrants in Los Angeles. *Urban Geography*, *35*(6), 822–851. https://doi.org/10.1080/02723638.2014.926634

Jones, K. (2014). 'It Was a Whirlwind. A Lot of People Made a Lot of Money': The Role of Agencies in Facilitating Migration from Poland into the UK between 2004 and 2000. *Central and Eastern European Migration Review*, *3*(2), 105–125.

Kalter, F. (2011). Social capital and the dynamics of temporary labour migration from Poland to Germany. *European Sociological Review*, *27*(5), 555–569. https://doi.org/10.1093/esr/jcq025

Kalter, F., & Kogan, I. (2014). Migrant Networks and Labor Market Integration of Immigrants from the Former Soviet Union in Germany. *Social Forces*, *92*(4), 1435–1456. https://doi.org/10.1093/sf/sot155

Kanas, A., van Tubergen, F., & van der Lippe, T. (2011). The role of social contacts in the employment status of immigrants. *International Sociology*, *26*(1), 95–122. https://doi.org/DOI:%252010.1177/0268580910380977

Kievit, R. A., Brandmaier, A. M., Ziegler, G., van Harmelen, A.-L., de Mooij, S. M. M., Moutoussis, M., Goodyer, I. M., Bullmore, E., Jones, P. B., Fonagy, P., Lindenberger, U., & Dolan, R. J. (2018). Developmental cognitive neuroscience using latent change score models: A tutorial and applications. *Developmental Cognitive Neuroscience*, *33*, 99–117. https://doi.org/10.1016/j.dcn.2017.11.007

Kracke, N., & Klug, C. (2021). Social Capital and Its Effect on Labour Market (Mis)match: Migrants' Overqualification in Germany. *Journal of International Migration and Integration*, *22*(4), 1573–1598. https://doi.org/10.1007/s12134-021-00817-1

Lancee, B. (2010). The Economic Returns of Immigrants' Bonding and Bridging Social Capital: The Case of the Netherlands1. *International Migration Review*, *44*(1), 202–226. https://doi.org/10.1111/j.1747-7379.2009.00803.x

Lancee, B. (2012). The economic returns of bonding and bridging social capital for immigrant men in Germany. *Ethnic and Racial Studies*, *35*(4), 664–683. https://doi.org/10.1080/01419870.2011.591405

Lancee, B. (2016). Job search methods and immigrant earnings: A longitudinal analysis of the role of bridging social capital. *Ethnicities*, *16*(3), 349–367. https://doi.org/10.1177/1468796815581426

Lancee, B., & Hartung, A. (2012). Turkish Migrants and Native Germans Compared: The Effects of Inter-Ethnic and Intra-Ethnic Friendships on the Transition from Unemployment to Work. *International Migration*, *50*(1), 39–54. https://doi.org/10.1111/j.1468-2435.2011.00736.x

Leschke, J., & Weiss, S. (2020). With a Little Help from My Friends: Social-Network Job Search and Overqualification among Recent Intra-EU Migrants Moving from East to West. *Work, Employment and Society*, *34*(5), 769–788. https://doi.org/10.1177/0950017020926433

Lin, N. (2001). *Social Capital: A Theory of Social Structure and Action*. Cambridge University Press.

Lubbers, M. J., Molina, J. L., & McCarty, C. (2007). Personal Networks and Ethnic Identifications: The Case of Migrants in Spain. *International Sociology*, *22*(6), 721–741. https://doi.org/10.1177/0268580907082255

Lubbers, M., Gijsberts, MI.L., Fleischmann F, & Maliepaard, M.I. (2018). *New Immigrant Survey—The Netherlands* (Version V2) [Dataset]. DANS Data Station Social Sciences and Humanities. https://doi.org/10.17026/DANS-22U-7KAD

McArdle., J. J. (2001). A latent difference score approach to longitudinal dynamic structural analysis. In R. Cudeck, S. du Toit, & D. Sörbom (Eds.), *Structural Equation Modelling: Present and Future.* Scientific Software International.

McGauran, K., de Haan, E., Scheele, F., & Winsemius, F. (2016). *Profiting from dependency*. SOMO & Fairwork. https://www.somo.nl/nl/profiting-from-dependency/

Ministerie van Sociale Zaken en Werkgelegenheid. (2024). *Verbeteren positie arbeidsmigranten—Buitenlandse werknemers—Rijksoverheid.nl*. Rijksoverheid.nl. https://www.rijksoverheid.nl/onderwerpen/buitenlandse-werknemers/verbeteren-positie-arbeidsmigranten

Moreno Galbis, E., Wolff, F.-C., & Herault, A. (2020). How helpful are social networks in finding a job along the economic cycle? Evidence from immigrants in France. *Economic Modelling*, *91*, 12–32. https://doi.org/10.1016/j.econmod.2020.05.017

Mouw, T. (2002). Racial differences in the effects of job contacts: Conflicting evidence from cross-sectional and longitudinal data. *Social Science Research*, *31*(4), 511–538. https://doi.org/10.1016/S0049-089X(02)00020-0

Mouw, T. (2003). Social Capital and Finding a Job: Do Contacts Matter? *American Sociological Review*, *68*(6), 868–898. https://doi.org/10.1177/000312240306800604

Munshi, K. (2003). Networks in the Modern Economy: Mexican Migrants in the U. S. Labor Market. *The Quarterly Journal of Economics*, *118*(2), 549–599. https://doi.org/10.1162/003355303321675455

Muthén, B., Kaplan, D., & Hollis, M. (1987). On Structural Equation Modeling with Data that are not Missing Completely at Random. *Psychometrika, 52*(3), 431–462. https://doi.org/10.1007/bf02294365

Nederlandse Arbeidsinspectie. (2016, July 18). *Uitzendwerk en Detachering*. https://www.nlarbeidsinspectie.nl/sectoren/uitzendwerk-detachering

Putnam, R. D. (2000). *Bowling alone: The Collapse and Revival of American Community.* Simon & Schuster.

Robone, S., Jones, A. M., & Rice, N. (2011). Contractual conditions, working conditions and their impact on health and well-being. *The European Journal of Health Economics*, *12*(5), 429–444. https://doi.org/10.1007/s10198-010-0256-0

Rüdel, J., & Steinmann, J.-P. (2024). 'With a little help from my educated friends': Revisiting the role of social capital for immigrants' labour market integration in Germany. *Comparative Migration Studies*, *12*(1), 7–30. https://doi.org/10.1186/s40878-024-00366-3

Ruhs, M., & Anderson, B. (2012). *Who Needs Migrant Workers?: Labour shortages, immigration, and public policy*. Oxford University Press.

Ryan, L. (2011). Migrants' Social Networks and Weak Ties: Accessing Resources and Constructing Relationships Post-Migration. *The Sociological Review*, *59*(4), 707–728. https://doi.org/10.1111/j.1467-954X.2011.02030.x

Ryan, L. (2022). The Direct and Indirect Role of Migrants' Networks in Accessing Diverse Labour Market Sectors: An Analysis of the Weak/Strong Ties Continuum. In E. Keskiner, M. Eve, &

L. Ryan (Eds.), *Revisiting Migrant Networks: Migrants and their Descendants in Labour Markets*. Springer International Publishing. https://doi.org/10.1007/978-3-030-94972-3

Ryan, L., Sales, R., Tilki, M., & Siara, B. (2008). Social networks, social support and social capital: The experiences of recent Polish migrants in London. *Sociology*, *42*(4), 672–690. https://doi.org/10.1177/0038038508091622

Seibel, V., & Van Tubergen, F. (2013). Job-Search Methods Among Non-Western Immigrants in the Netherlands. *Journal of Immigrant & Refugee Studies*, *11*(3), 241–258. https://doi.org/10.1080/15562948.2013.801727

Siegmann, K. A., & Williams, T. (2020). *Are agri-food workers only exploited in southern Europe? : Case studies on migrant labour in Germany, The Netherlands, and Sweden* (pp. 13–21). Open Society Foundations. https://cadmus.eui.eu/entities/publication/0aa6de69-5a1e-59e2-bf6b-d2349f53f804

Snel, E., Engbersen, G., & Leerkes, A. (2006). Transnational Involvement and Social Integration. *Global Networks*, *6*, 285–308. https://doi.org/10.1111/j.1471-0374.2006.00145.x

Strockmeijer, A., De Beer, P., & Dagevos, J. (2017). Mobiliteit binnen de perken: Zeer geringe positieverbetering van werknemers uit Oost-Europa bij een langer werkverleden. *Tijdschrift voor Arbeidsvraagstukken*, *33*(4). https://doi.org/10.5117/2017.033.004.002

Strockmeijer, A., de Beer, P., & Dagevos, J. (2019). Should I stay or should I go? What we can learn from working patterns of Central and Eastern European labour migrants about the nature of present-day migration. *Journal of Ethnic and Migration Studies*, *45*(13), 2430–2446. https://doi.org/10.1080/1369183X.2018.1562326

Szytniewski, B., & van der Haar, M. (2022). Mobility power in the migration industry: Polish workers' trajectories in the Netherlands. *Journal of Ethnic and Migration Studies*, *48*(19), 4694–4711. https://doi.org/10.1080/1369183X.2022.2061931

Vacca, R., Bilecen, B., & Lubbers, M. J. (2025). Social networks in migration and migrant incorporation: New developments and challenges. *International Migration*, *63*(1), e13373. https://doi.org/10.1111/imig.13373

Van der Gaag, M. P. J., & Snijders, T. A. B. (2004). Proposals for the Measurement of Individual Social Capital. In H. Flap & B. Volker (Eds.), *Creation and Returns of Social Capital* (pp. 199–218). Routledge.

van Ostaijen, M., Faber, M., Scholten, P., & Engbersen, G. (2015). *Social consequences of CEE migration*. Erasmus University Rotterdam. https://repub.eur.nl/pub/78009

Appendix

Table 1: Missing data analysis: descriptive statistics of respondents with complete data vs. respondents with missing data

	Wave 1 **Complete cases**	**Incomplete cases**	**Wave 2** **Complete cases**	**Incomplete cases**	**Wave 3** **Complete cases**	**Incomplete**	**Wave 4** **Complete cases**	**Incomplete cases**
Country of birth								
Poland	172 (83.90%)	1,474 (76.41%)	172 (83.90%)	1,474 (76.41%)	172 (83.90%)	1,474 (76.41%)	172 (83.90%)	1,474 (76.41%)
Bulgaria	33 (16.10%)	455 (23.59%)	33 (16.10%)	455 (23.59%)	33 (16.10%)	455 (23.59%)	33 (16.10%)	455 (23.59%)
Gender								
Male	110 (53.92%)	826 (42.86%)	106 (51.71%)	297 (38.22%)	107 (52.20%)	118 (30.65%)	108 (52.68%)	50 (22.52%)
Female	94 (46.08%)	1,101 (57.14%)	99 (48.29%)	480 (61.78%)	98 (47.80%)	267 (69.35%)	97 (47.32%)	172 (77.48%)
Education								
Low education (less than primary – upper secondary)	36 (17.65%)	431 (22.65%)	36 (17.65%)	431 (22.65%)	36 (17.65%)	431 (22.65%)	36 (17.65%)	431 (22.65%)
Medium education (upper secondary – non-tertiary)	60 (29.41%)	683 (35.89%)	60 (29.41%)	683 (35.89%)	60 (29.41%)	683 (35.89%)	60 (29.41%)	683 (35.89%)
High education (short- cycle tertiary – doctoral or equivalent)	108 (52.94%)	789 (41.46%)	108 (52.94%)	789 (41.46%)	108 (52.94%)	789 (41.46%)	108 (52.94%)	789 (41.46%)
Mean language skills (SE) 0= poor Dutch language skills – 3= very good Dutch language skills	0.88 (0.60)	0.94 (0.63)	1.16 (0.58)	1.21 (0.66)	1.29 (0.60)	1.40 (0.68)	1.38 (0.62)	1.59 (0.70)
Job security								
Casual contract	12 (5.85%)	140 (9.05%)	8 (3.90%)	35 (7.13%)	1 (0.49%)	11 (4.42%)	0 (0.00%)	8 (6.61%)
Temporary contract	124 (60.49%)	970 (62.70%)	105 (51.22%)	281 (57.23%)	87 (42.44%)	128 (51.41%)	60 (29.27%)	53 (43.80%)
Permanent contract	69 (33.66%)	437 (28.25%)	92 (44.88%)	175 (35.64%)	117 (57.07%)	110 (44.18%)	145 (70.73%)	60 (49.59%)
Irregular hours								
Yes, regularly	49 (23.90%)	361 (22.65%)	56 (27.32%)	121 (23.82%)	49 (23.90%)	70 (27.45%)	53 (25.85%)	32 (25.81%)
Yes, sometimes	97 (47.32%)	808 (50.69%)	105 (51.22%)	254 (50.00%)	102 (49.76%)	108 (42.35%)	99 (48.29%)	56 (45.16%)
No, never	59 (28.78%)	425 (26.66%)	44 (21.46%)	133 (26.18%)	54 (26.34%)	77 (30.20%)	53 (25.85%)	36 (29.03%)
Hazardous work								
Yes, regularly	15.00 (7.32%)	101 (6.36%)	15 (7.32%)	25 (4.90%)	25 (12.20%)	20 (7.84%)	25 (12.20%)	6 (4.80%)

Yes, sometimes	64.00 (31.22%)	522 (32.87%)	69 (33.66%)	164 (32.16%)	75 (36.59%)	73 (28.63%)	73 (35.61%)	35 (28.00%)
No, never	126.00 (61.46%)	965 (60.77%)	121 (59.02%)	321 (62.94%)	105 (51.22%)	162 (63.53%)	107 (52.20%)	84 (67.20%)
Physical work								
Yes, regularly	49 (23.90%)	449 (28.29%)	46 (22.44%)	134 (26.27%)	51 (24.88%)	61 (23.92%)	52 (25.37%)	36 (29.03%)
Yes, sometimes	96 (46.83%)	779 (49.09%)	100 (48.78%)	230 (45.10%)	101 (49.27%)	125 (49.02%)	89 (43.41%)	48 (38.71%)
No, never	60 (29.27%)	359 (22.62%)	59 (28.78%)	146 (28.63%)	53 (25.85%)	69 (27.06%)	64 (31.22%)	40 (32.26%)
Satisfaction with earnings								
Very dissatisfied	8 (3.90%)	68 (4.35%)	7 (3.41%)	20 (3.92%)	9 (4.39%)	5 (2.00%)	8 (3.90%)	5 (4.07%)
Somewhat dissatisfied	16 (7.80%)	122 (7.81%)	22 (10.73%)	33 (6.47%)	23 (11.22%)	36 (14.40%)	28 (13.66%)	19 (15.45%)
Neither satisfied nor dissatisfied	28 (13.66%)	292 (18.68%)	37 (18.05%)	90 (17.65%)	30 (14.63%)	47 (18.80%)	38 (18.54%)	27 (21.95%)
Somewhat satisfied	107 (52.20%)	768 (49.14%)	92 (44.88%)	256 (50.20%)	112 (54.63%)	133 (53.20%)	101 (49.27%)	59 (47.97%)
Very satisfied	46 (22.44%)	313 (20.03%)	47 (22.93%)	111 (21.76%)	31 (15.12%)	29 (11.60%)	30 (14.63%)	13 (10.57%)
Contact frequency with co-ethnics								
Never	9 (4.39%)	97 (5.05%)	5 (2.44%)	39 (5.05%)	7 (3.41%)	19 (5.00%)	7 (3.41%)	13 (5.94%)
Less often (than several times a year)	16 (7.80%)	153 (7.97%)	23 (11.22%)	67 (8.68%)	11 (5.37%)	33 (8.68%)	18 (8.78%)	14 (6.39%)
Several times a year	18 (8.78%)	133 (6.93%)	29 (14.15%)	84 (10.88%)	30 (14.63%)	44 (11.58%)	34 (16.59%)	32 (14.61%)
A few times a month	55 (26.83%)	421 (21.93%)	61 (29.76%)	184 (23.83%)	70 (34.15%)	108 (28.42%)	63 (30.73%)	68 (31.05%)
Several times a week	32 (15.61%)	345 (17.97%)	35 (17.07%)	150 (19.43%)	35 (17.07%)	65 (17.11%)	33 (16.10%)	36 (16.44%)
Everyday	75 (36.59%)	771 (40.16%)	52 (25.37%)	248 (32.12%)	52 (25.37%)	111 (29.21%)	50 (24.39%)	56 (25.57%)
Contact frequency with Dutch								
Never	41 (20.00%)	329 (17.16%)	28 (13.66%)	117 (15.12%)	28 (13.66%)	51 (13.46%)	29 (14.15%)	25 (11.47%)
Less often (than several times a year)	33 (16.10%)	372 (19.41%)	58 (28.29%)	146 (18.86%)	36 (17.56%)	62 (16.36%)	39 (19.02%)	44 (20.18%)
Several times a year	27 (13.17%)	210 (10.95%)	32 (15.61%)	105 (13.57%)	38 (18.54%)	53 (13.98%)	50 (24.39%)	29 (13.30%)
A few times a month	46 (22.44%)	336 (17.53%)	41 (20.00%)	136 (17.57%)	43 (20.98%)	78 (20.58%)	46 (22.44%)	41 (18.81%)
Several times a week	29 (14.15%)	323 (16.85%)	25 (12.20%)	129 (16.67%)	27 (13.17%)	74 (19.53%)	18 (8.78%)	38 (17.43%)
Everyday	29 (14.15%)	347 (18.10%)	21 (10.24%)	141 (18.22%)	33 (16.10%)	61 (16.09%)	23 (11.22%)	41 (18.81%)