A multilevel path analysis of social networks and social interaction in the neighbourhood

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Abstract
The topic of neighbourhood-based social interactions has gained attention in the last decades in the light of urban policies that aim to deal with problems regarding social segregation and exclusion, quality of life and liveability in urban areas. Social interactions are expected to play an important role in dealing with these problems. However, empirical studies investigating to which extent neighbourhood characteristics can improve social contacts among residents are scarce and inconclusive. Therefore, this paper studies the role of socio-demographics and neighbourhood characteristics in the formation of social network ties and social interactions with neighbours. Based on data collected in 2011 in 70 different neighbourhoods of Eindhoven in the Netherlands in a survey among 751 respondents these relationships are analysed using a multi-level path analysis approach. The results indicate that neighbourhood-based contacts are influenced by personal and household characteristics, such as education, income, work status, ethnicity, household composition, and years at the current address. Neighbourhood characteristics are not found to affect social network size, the share of neighbours in the network or the frequency of interaction with neighbours.

Keywords
Personal networks, multi-level, path analysis, neighbourhood effects, social contact

1. Introduction

Social contacts are important for people's wellbeing. The local neighbourhood can provide opportunities for social contacts. Although the role of neighbourhoods in significant social ties is declining (e.g. Wellman, 1979; 2001; Guest and Wierzbicki, 1999), Bridge (2002) suggests that "neighbourhood ties continue to be important for a sizeable proportion of the population".

In sociology there's a rich amount of literature on the degree to which social networks are neighbourhood based. For an in-depth review, we refer to Bridge (2002). However, most of this literature does not focus on the effect of the (spatial) characteristics of the neighbourhood on social interaction among residents, whereas these characteristics are of special interest from the perspective of housing and urban planning.

In the field of housing and urban planning in Western European countries the topic of neighbourhood-based social interactions has gained attention in the last decades in the light of urban renewal policies (Forrest and Kearns, 2001). These policies aim to deal with a variety of urban problems such as quality of housing and public space, unemployment, poverty, liveability and social segregation and exclusion. In these policies, social interactions are expected to play an important role in dealing with these problems. This is for instance underlined by Kleinhans (2004) who reviewed the literature on the social implications of housing diversification in urban renewal projects. According to Kleinhans (2004) "almost all the assumed benefits of housing diversification and social mix are expected to arise from social interactions". He concludes however, that lifestyle is far more important than neighbourhood characteristics such as tenure to explain social interaction.

Overall, empirical evidence for effects of neighbourhood characteristics on social interaction with neighbours is scarce and inconclusive (Atkinson and Kintrea, 2001; Kleinhans, 2004; Galster, 2007; Pinkster and Völker, 2009). This paper therefore aims to contribute to our knowledge of neighbourhood-based social contacts, by studying the role of socio-demographics and neighbourhood characteristics in the formation of social network ties and social interactions with neighbours. These relationships are studied using a multi-level path analysis approach. The analyses are based on data collected in 2011 in 70 different neighbourhoods of Eindhoven in the Netherlands in a survey among 751 respondents.

The structure of the paper is as follows. The next section describes the literature on the factors influencing neighbourhood-based social contacts. Section 3 presents the data collection and descriptive statistics. In section 4 the path analysis results are presented. Finally, Section 5 contains the conclusions and discussion.

2. Factors influencing neighbourhood-based social contacts

This section reviews the existing literature on the factors that may affect the formation of social network ties and social interactions with neighbours.

Regarding neighbourhood characteristics, the literature suggests that neighbourhood-based social contact may be affected by neighbourhood income (which is also related to ethnicity), urban density and residential mobility. For instance, in a large survey of personal networks in northern California, Fischer (1982) found that in low-income neighbourhoods the contact frequency between neighbours is lower than in higher income neighbourhoods. According to Fischer this is due to the fact that there is more variety with regard to race, ethnicity and occupation in low-income neighbourhoods. This seems to suggest that similarity in background characteristics enhances neighbourhood contacts (Völker and Flap, 2007), which contradicts the assumption that social mix would lead to more neighbourhood-based social interaction.

Comparing the role of local relationships and social support in a low-income and a socio-economic mixed neighbourhood, Pinkster and Völker (2009) found that people living in

a low-income neighbourhood have fewer resources in terms of accessed prestige. However, they found no difference regarding social support for dealing with everyday problems. Similarly, Van Eijk (2010) studying whether living in a poor neighbourhood results in network poverty, concludes that network poverty is not so much related to spatial characteristics but rather to a lack of participation in certain settings such as study, work, leisure and associations.

Studying the effects of social-structural neighbourhood characteristics on the relative size and the composition of neighbouring networks of elderly people in the Netherlands Thomése and van Tilburg (2000) found that people living in neighbourhoods with a larger degree of urbanisation had a smaller proportion of neighbours in their social network. This is in line with Fischer's (1982) findings. Residential mobility in the neighbourhood was also associated with smaller neighbouring networks.

In addition, network localness has been found to be associated with personal or household characteristics such as socioeconomic status. The results are sometimes inconsistent though. For instance, Fischer (1982) found social networks of low-income, low educated and minority residents to be more locally oriented. This may be related to the fact that activities and transport cost money, resulting in a smaller action radius for people with a lower income (Van Beckhoven and Van Kempen, 2003). The level of income is associated with work status, level of education and ethnicity. Van Eijk (2010) found that low educated people had a larger share of local ties in their network. However, the number of local ties was similar. It was the number of non-local network members that was higher for higher educated people. On the other hand, Van der Poel (1993) found that higher educated people have more neighbours in their networks than lower educated people.

Age may also be related to neighbourhood orientation. Older adults are often seen as being particularly dependent on neighbouring networks. Völker and Flap (2007) indeed found that older people are more likely to have neighbours in their social network. However, Thomése and van Tilburg (2000) did not find age to affect the proportion of neighbours in people's network.

Time spent in the neighbourhood increases the chances of meeting neighbours (Völker and Flap, 2007; Guest and Wierzbicki, 1999). There are different conditions that cause people to spend more time in the area where they live. For instance, people who do not work are likely to spend more time at home than people who work full time. The same goes for people with young children. In addition, children's school can serve as a setting to develop and maintain locality-based ties (Van Beckhoven and van Kempen, 2003; Van Eijk, 2010). Völker and Flap (2007) also found the presence of primary schools to increase the likelihood of including neighbours in the personal network.

In a previous study we also found that involvement in clubs or voluntary associations results in a larger social network (Van den Berg et al. 2012). As clubs are often locally based, this may indirectly increase the frequency of contact with neighbours.

Finally, the degree to which people have neighbourhood-based social contacts might be also related to their extra-neighbourhood contacts. Völker and Flap (2007) argue that "if one has no other members in their personal network, neighbours become the first (and only) choice". However, van Eijk (2010) concludes that "resource-poor people with small networks do not seem to compensate for their small network by forming more ties with fellow-residents".

This brief overview of literature suggests that neighbourhood-based social contact may be related to a number of neighbourhood and personal characteristics. However, the results from different studies are inconclusive. This calls for more empirical evidence on the effects of personal and neighbourhood characteristics on social interaction with neighbours.

This study will analyse these relationships based on data collected in Eindhoven, the Netherlands. The next section discusses the data collection for this study.

3. Data collection and descriptive statistics

The data used for this study were collected in May 2011 in 70 neighbourhoods in Eindhoven. The data collection instrument consisted of a survey on quality of life aspects of individuals in the area of residence. People aged 18 or over could participate.

For the sample a stratified sampling technique was used. The city was divided into neighbourhoods (based on the arrangement of the municipality), in which equal numbers of individuals were contacted. To recruit respondents, a personal approach was employed by visiting them at home. The addresses within these neighbourhoods were chosen randomly. If residents were not at home, the addresses were skipped. The visits took place at varying times of day, also in the evening, to prevent an underrepresentation of working people. The personal approach was employed to increase respondent's participation. However, it may have caused some bias in the sample of people who were not home. In total, 751 useful questionnaires were collected.

Several socio-demographic variables were collected in the questionnaire. In addition, neighbourhood characteristics were obtained from Statistics Netherlands (CBS, 2012). Table 1 shows the sample characteristics. The sample is fairly representative of the Eindhoven population, although lower educated people and immigrants are somewhat underrepresented.

Table 1: Sample characteristics (N=751 respondents)

	Mean	St. dev.
Personal characteristics		
Age	47.11	16.86
Full time work: ≥36 hours (dummy)	0.23	
No work (dummy)	0.42	
Low income: < € 1000,- per month after tax (dummy)	0.11	
High income > € 3000,- per month after tax (dummy)	0.29	
Low education: primary (dummy)	0.07	
High education: BSc or higher (dummy)	0.38	
Household with child(ren) under 18 (dummy)	0.40	
Club memberships (nr)	0.96	1.20
Western immigrant (dummy)	0.04	
Non-western immigrant (dummy)	0.06	
Years in current address	13.90	12.81
Neighbourhood characteristics		
Mean household income in neighbourhood (x €1000)	23.91	5.66
% non-western immigrants in neighbourhood	16.34	9.02
Urban: >2500 addresses per km^2 (dummy)	0.39	

The aim of this paper is to study the role of socio-demographics and neighbourhood characteristics in the formation of social network ties and social interactions with neighbours. In the analyses three dependent variables are used: social network size, the share of neighbours in the social network and the frequency of interaction with neighbours.

Think about the people you feel very close to or somewhat close to.

Very close: these are people - with whom you discuss important matters,
- or you regularly keep in contact with,
- or who are there for you if you help.

Somewhat close: these are people that are more than just casual acquaintances, but not very close.

How many persons of the following categories are you very close to and how many persons are you somewhat close to?

	Very close	**Somewhat close**
Direct relatives (parents, brothers, sisters, children)	……	……
Other relatives	……	……
Colleagues or fellow students	……	……
Fellow club or association members	……	……
Neighbours	……	……
Other friends not mentioned above	……	……

Figure 1: Measuring social network size and share of neighbours

Figure 1 shows the question that was used to measure social network size and the share of neighbours in the social network. This method used to gather the characteristics of the respondent's social networks is known as the summation method. See McCarty et al. (2000) for details.

The share of neighbours in the social network is an indicator for whether and to what extent people form relationships with fellow residents (Van Eijk, 2010). The total number of very close and somewhat close ties is used as the measure for social network size. On average, the respondents have a network size of 24.85 alters (st.dev. 25.68), which is comparable to other studies that used the same name generators (Hogan et al., 2007; Van den Berg et al., 2009). The average number of neighbours in the social network is 2.80 (st.dev. 4.89). Out of the social network ties with neighbours 30% is very strong and 70% somewhat strong.

The share of neighbours in the social network is the percentage of neighbours (very close and somewhat close) in the total social network. The average percentage of neighbours in the respondents' social network is 10.14% (st. dev. 13.50). Although the size and composition of the elicited networks depends on the name generating questions that are used, neighbours generally constitute 8% to 16% of a person's social network (e.g. Fischer, 1982; Van der Poel, 1993; Völker and Flap, 2007; van den Berg et al., 2009).

However, almost half of the respondents recorded no neighbours as social network members. This finding is again in line with Völker and Flap (2007) who report that 48% of the respondents in their study have no neighbours in their social network. This finding may partially be due to the definition of the question, which does not allow overlap between the categories. For instance, relatives or co-workers who also live in the same neighbourhood, will probably not be recorded as neighbours.

Moreover, not considering neighbours to be social network members as defined by the name generators, does not mean these people never interact with their neighbours. As can be seen in Table 2 only 6.5% of the respondents indicated to never interact with their neighbours. The largest share of respondents indicated to interact with their neighbours several times per week.

For the purpose of the analysis, we regard this ordinal variable as a continuous variable, representing the number of interactions per month. We therefore recoded this

variable into the middle values of the categories (0; 1; 2.5; 4; 12 and 24 times per month). Based on this recoded measure, the mean frequency of interaction with neighbours is 9.19 (st. dev. 8.18).

Table 2: Frequency of interaction with neighbours (N=751 respondents)

Frequency of interaction	N	%
Never (0)	49	6.5
Once a month or less (1)	112	14.9
2 or 3 times per month (2.5)	89	11.9
Once a week (4)	130	17.3
Several times per week (12)	237	31.6
(almost) every day (24)	133	17.7

4. Methods and results

The question posed in this paper requires a method that can capture the relationships between several dependent and independent variables. Path analysis is a method that meets this requirement. Using path analysis the effects of the explanatory variables on the dependent variables, as well as the relationships between the dependent variables can be estimated simultaneously. In path analysis, both direct and indirect effects can be calculated. These characteristics make that path analysis is more useful than linear regression analysis.

Path analysis is a special case of structural equation modelling (SEM). Whereas SEM can deal with measured (or observed) variables and latent variables (also known as factors, constructs or unobserved variables), path analysis deals only with measured variables. In this study we use path analysis, because the variables all refer to characteristics or behaviour that is observed.

We estimate and compare two models: a single level model and a multi-level model. The latter takes into account the hierarchical structure of the data (multiple respondents per neighbourhood). Whereas the single level model treats the respondents as independent observations, in the multi-level the respondents that belong to the same neighbourhood are treated in clusters by allowing for residual components at each level. For an in-depth review of multi-level (structural equation) models we refer to (Hox and Roberts 2010).

The path analysis models are estimated using the statistical software package LISREL (Jöreskog and Sörbom, 2001). Despite non-normality in the data, the maximum likelihood method is used to estimate the models. The exogenous socio-demographic and neighbourhood characteristics are allowed to be correlated in the models. As a first step in building the single level model, all paths from the exogenous variables to the endogenous variables, as well as paths between the endogenous variables were entered. Relationships that were not significant at the 0.1 significance level were removed in a stepwise procedure. This resulted in model 1. In model 2 the same relationships are entered, however, in this model the respondents from the same neighbourhood are clustered.

The unstandardized coefficients of direct and total effects of the final model are shown in Table 3. The total effects are the direct effects (X causes Y) plus indirect effects (X causes Z, which in turn causes Y).

Table 3: Path analysis model estimates (unstandardized effects)

		Model 1			Model 2 (multilevel)		
		Network size	% neighbours	Interactions per month	Network size	% neighbours	Interactions per month
Network size	direct		0.04 **	0.03 ***		0.05 **	0.03 ***
	total		0.04 **	0.04 ***		0.05 **	0.04 ***
% neighbours	direct			0.16 ***			0.16 ***
	total			0.16 ***			0.16 ***
Age	direct	-0.14 **			-0.10 *		
	total	-0.14 **	-0.01	-0.01 **	-0.10 *	0.00	0.00 **
Full time work	direct			-2.21 ***			-2.15 ***
	total			-2.21 ***			-2.15 ***
No work	direct		2.88 ***			2.07 *	
	total		2.88 ***	0.46 ***		2.07 *	0.33 ***
Low income	direct			-2.04 **			-2.49 **
	total			-2.04 **			-2.49 **
High income	direct	8.02 ***			8.46 **		
	total	8.02 ***	0.31 *	0.30 **	8.46 **	0.38 *	0.34 **
Low education	direct			2.93 ***			2.64 **
	total			2.93 ***			2.64 **
High education	direct			-1.16 *			-1.59 **
	total			-1.16 *			-1.59 **
Child(ren)	direct		4.45 ***	1.25 **		4.33 ***	1.35 **
	total		4.45 ***	1.97 **		4.33 ***	2.03 ***
Club memberships	direct	5.13 ***			5.32 ***		
	total	5.13 ***	0.20 **	0.19 ***	5.32 ***	0.24 **	0.22 ***
Western immigrant	direct		-7.93 ***			-8.52 ***	
	total		-7.93 ***	-1.27 ***		-8.52 ***	-1.34 ***
Non-western imm.	direct		-4.05 *			-4.53 **	
	total		-4.05 *	-0.65 *		-4.53 **	-0.71 *
Years in address	direct		0.13 ***	0.08 ***		0.13 ***	0.07 ***
	total		0.13 ***	0.10 ***		0.13 ***	0.09 ***
Neighb. income	direct	0.29 *			0.65		
	total	0.29 *	0.01	0.01	0.65	0.03	0.03
% non-western imm.	direct		-0.12 **			-0.11	
	total		-0.12 **	-0.02 **		-0.11	-0.02
Urban	direct			-0.94*			-1.28
	total			-0.94*			-1.28
R^2		0.10	0.07	0.16	0.10	0.06	0.15
R^2 reduced form		0.10	0.06	0.08	0.10	0.05	0.08

The modelling results indicate that both social network size and the share of neighbours in the network have a positive effect on the frequency of interaction with neighbours. This is a plausible finding. However, the effects are only small. One extra social network member results in 0.03 or 0.04 extra social interactions with neighbours per month. If the share of neighbours increases with 1%, the frequency of interaction per month increases with 0.16. The share of neighbours in the network is positively affected by the size of the social network, however, the effect is very small.

Regarding the effects of socio-demographics on social network size, the results show a negative effect of age. Income has a positive effect on social network size. Involvement in clubs or associations also results in a larger social network, with more than 5 extra network members per club membership.

The share of neighbours in people's social network is found to be higher for people who do not work and people with children. These effects were expected as these groups tend to spend more time at home (and in the neighbourhood). As expected, the number of years

one has been living at the current address has a positive effect on the share of neighbours in the social network. Both western and non-western immigrants are found to have a smaller share of neighbours in their social network.

Finally, regarding the frequency of interaction with neighbours, direct effects were found for some of the socio-demographic variables. People who work full time are found to have more than 2 interactions per month less with their neighbours. In line with that, low educated people are found to have more social interactions with their neighbours and high educated people contact their neighbours less often. On the other hand, low income is found to reduce the number of interactions with neighbours per month with 2 to 2.5. As expected, people with children are found to interact more often with their neighbours. A positive effect is also found for the number of years living at the same address.

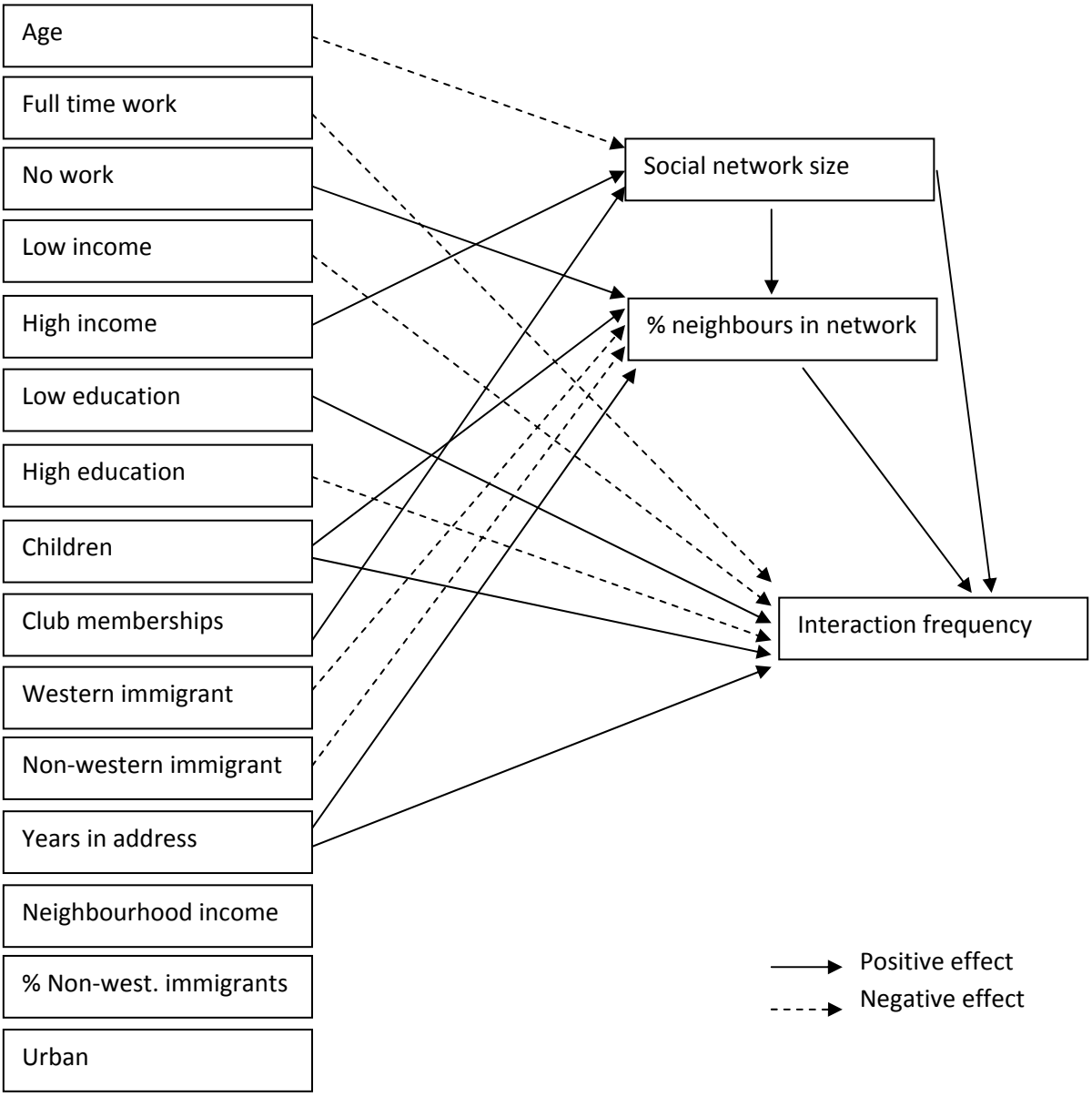

Figure 2: Path analysis model results

Regarding the neighbourhood characteristics, a number of different variables were tested in the single-level model, namely neighbourhood income, urban density, housing tenure, residential mobility and ethnicity. Three variables were found to have a significant effect in this model. In the single level model, the mean income of households in the neighbourhood is found to have a positive effect on social network size. However, in the multi-level model this effect is no longer significant.

In addition, in the single level model the percentage of non-western immigrants in the neighbourhood has a negative effect on the share of neighbours one has in his social network. However, in the multi-level model this effect becomes non-significant again.

And finally, a negative effect on the frequency of social interaction with neighbours is found for people living in neighbourhoods with a density of more than 2500 addresses per km^2. Again, this effect is not significant in the multi-level model.

The results show that, although the single level model shows some significant effects, none of the neighbourhood characteristics have a significant effect in the multi-level model. This finding shows the importance of using multilevel models for data with a hierarchical structure to prevent us from drawing premature conclusions. The multi-level model shows that urban planners and policy makers should be very cautious regarding the wide held assumption that an adaptation of neighbourhood characteristics (for instance through urban renewal) can lead to increasing social interaction among neighbours.

The direct effects that are significant at the 0.1 significance level in the multi-level model are shown in Figure 2. Table 4 shows the Goodness of fit statistics of both models. The overall fit of both models appears quite good. Chi Square divided by the model degrees of freedom has been suggested a useful measure and rules of thumb suggest that for correct models this measure should be smaller than 2 (Golob, 2001) or at least smaller than 5, but preferably around 1 (Washington et al., 2003). According to this rule of thumb, the models have a good fit with a value of 0.777 and 0.699. Another goodness-of-fit measure which is based on the Chi-square is the root mean square error of approximation (RMSEA), which measures the discrepancy per degree of freedom. The value should preferably be less than 0.05 (Golob, 2001). The RMSEA of 0.0 also suggests that the models fit the data well.

Table 4: Goodness of fit statistics

	Model 1	**Model 2**
Degrees of Freedom	28	436
Full Information ML Chi-Square	21.76	304.58
Chi-Square / Degrees of Freedom	0.777	0.699
Root Mean Square Error of Approximation (RMSEA)	0.0	0.0
90 Percent Confidence Interval for RMSEA	0.0; 0.019	0.0; 0.0
Normed fit index	0.99	
-2ln(L) for the saturated model		27221.912
-2ln(L) for the fitted model		27526.488

5. Conclusions and discussion

This paper has aimed at increasing our understanding of the factors influencing neighbourhood-based social contacts. Based on survey data collected in the Netherlands a path analysis approach was used to analyse social network size and the share of neighbours in the social network, as well as the frequency of social interaction with neighbours. The

exogenous variables in the models are personal socio-demographics and neighbourhood characteristics.

The results indicate that socio-demographics are more important than neighbourhood characteristics in explaining neighbourhood-based social contact. The share of neighbours in the social network is larger for people who spend more time at home (older people, people with children and people who do not work) and smaller for immigrants.

People who spend more time at home and who have been living longer at the current address also have higher contact frequencies with their neighbours. Regarding socio-economic status, the results are mixed. A higher level of education was found to have a negative effect on interaction frequency with neighbours, whereas income was found to have a positive effect.

The effects of neighbourhood characteristics are limited. Whereas some effects are found in the single level model, neighbourhood characteristics are not found to affect social network size, the share of neighbours in the network or the frequency of interaction with neighbours in the multilevel model. This finding is at variance with the assumption that an adaptation of neighbourhood characteristics (for instance through urban renewal) can lead to increasing social interaction among neighbours. In addition, the different findings regarding neighbourhood characteristics in both models shows the importance of using multilevel models for data with a hierarchical structure.

Although the analysed links can help to better understand neighbourhood-based social contacts, a number of aspects deserve further research. For instance, we did not differentiate between different types of social interaction with neighbours, as the data did not include this information. However, different types of interaction, such as saying hello in the street, borrowing things or visiting may differ substantially in intensity and importance for people.

Moreover, the question on the number of social network members did not allow for overlap between the different categories, whereas it is possible that relatives, co-workers or fellow club members are also neighbours. This should be kept in mind when interpreting the results for share of neighbours in the social network.

Finally, although we tested a number of neighbourhood characteristics, such as neighbourhood income, urban density, housing tenure, residential mobility and ethnicity, there might be other spatial characteristics that might affect neighbourhood-based social contacts. In future research we therefore aim to identify these characteristics, for instance by studying the role public space and amenities in the neighbourhood for social interaction.

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