Social Interaction and Sickness Absence

Assar Lindbeck, Mårten Palme and Mats Persson

Abstract

It is today generally acknowledged that social norms are important for moral hazard in social insurance systems. In this paper we study whether local variation in sickness absence can be explained by local variation in norms concerning benefit dependency – formed by social interaction on the neighborhood level. A well known methodological problem in analyses of this issue is how to disentangle the effects of individual sorting from the causal effects of group absence behavior on individual behavior. We use four different empirical approaches to deal with this issue. Each relies on an identifying assumption, which can be questioned. Still, all approaches separately indicate that the variation in the data is consistent with the hypothesis that social norms and group behavior are important for individual sickness absence.

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1. Introduction

Individual economic behavior is influenced not only by interaction through economic incentives and markets, but also by social interaction outside the market system. While such interaction, including the role of social norms, has been extensively analyzed theoretically during the last decade, empirical analysis in this field encounters serious difficulties. An obvious reason is that norms are intrinsically difficult to measure. In empirical studies it is therefore often necessary to rely on indicators of the operation of social norms. But this raises basic problems of how to separate social interaction from other types of correlation between individual behavior and group behavior. We discuss two such correlations that may be confused with social interaction. First, and most trivially, a certain group individuals, for instance those living in a specific geographical area, may behave similarly simply because of similar observable socioeconomic factors. Second, “autonomous” behavior of individuals (hence behavior not induced by social interaction) may be correlated because of similar non-observable individual characteristics (for instance as a result of selection) or because of non-observed similarities in their environment. The second point raises the problem of separating the causal effects of group behavior on individuals from unobserved, or insufficiently measured, individual or environment characteristics.

These problems are paramount in the analysis of social programs, since moral hazard in the context of such programs may be influenced by social norms. Although this possibility has been theoretically analyzed in a number of papers, for instance, in Lindbeck, Nyberg and Weibull (1999), there is very little empirical analysis of the matter. In the present paper, we use Swedish data to study one type of social insurance, namely sick pay insurance, in order to trace the effects of social norms on individual behavior. Sick pay insurance, which replaces foregone earnings due to temporary health deficiencies, is one of Sweden’s most important social programs. In recent years, the average employee in Sweden has claimed such sickness benefits for about 25 days per year, and the number of days has roughly doubled during the last decade. A puzzling feature of this explosive development is that it happened without any major changes in the replacement rates or eligibility rules. In recent years, a number of observers have hypothesized that this increase is related to changes in attitudes and norms concerning the conditions under which one may claim sickness benefits. There are also huge

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1 Manski (2000) has made a somewhat similar distinction, between what he calls “contextual interactions” and “correlated effects”.
variations across regions, and across neighborhoods, in the share of individuals claiming benefits. In this paper we exploit such local variation in order to find out whether local social norms may be part of the explanation of these variations. We thereby focus on the role of peer groups, defined by individuals living in the same neighborhood, and we use four different approaches to trace the influence of local social norms:

1. We investigate whether sickness absence of public-sector employees affects the behavior of neighbors employed in the private sector, and vice versa.
2. We estimate a diffusion model of the transmission of high-absence behavior in analogy with the transmission of innovations and of contagious diseases.
3. We ask whether immigrants tend to adjust their sick-absence behavior to the behavior of natives in their neighborhood.
4. We analyze the interaction between neighborhoods and workplaces, asking whether it is more likely that you are influenced by the absence behavior of your neighbors if they are also your workmates.

Our study is partly inspired by attitude studies on sick leave behavior. For instance, in a Swedish study by Modig and Broberg (2002), about 60 percent of the respondents regard it as OK to call sick without being so, e.g., due to family problems, a poor work environment, or dislike of their job or their boss. Other attempts to measure attitudes towards sickness absence have been presented in an anthology published by Palmer (2006). With the reservation that such attitudes are difficult to measure, the authors nevertheless find evidence that they are important for regional variations in absence (see in particular Olsson, 2006). While attitude studies may yield important insights on the motives for individual behavior, we have chosen a fundamentally different approach, since we study revealed rather than stated preferences.

There are also other econometric studies of sickness absence in Sweden. For instance, Ljunge (2005) found that young cohorts had a 25 percentage points higher incidence of sickness absence than cohorts born 20 years earlier – controlled for other likely influences. There are also three studies showing that short-term sickness absence in Sweden has increased

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2 A study with similar results was commissioned by the National Insurance Board (cf. Refina, 2005).
3 Incidence of sickness is in that study measured as the proportion of the population having at least one paid sick day during a year. The study controls for demographic variables (age, gender, education and family composition), income and business cycle factors.
significantly among men when major sports events are shown on television. Another indication of changing norms in connection with sick leave insurance is that mass sickness absence has been used as a tool in labor-market conflicts – even by police officers.

2. The data

Our analysis relies on an exceptional Swedish data set. It combines individual sick absence data, from the Swedish National Insurance Agency with a large number of socio-economic variables obtained from the database LISA, compiled by Statistics Sweden. In addition to data on numerous individual characteristics, it includes information on local neighborhoods and workplaces, allowing us to characterize all individuals on each workplace and in each neighborhood in the country.

One advantage of this dataset is that it covers the entire population in Sweden, referring to conditions in 2000 and 2001. A conceivable disadvantage is that it only covers spells of absence longer than 10 days. It would, of course, have been of great interest to have access also to data on shorter spells, but if one wants to exploit the rich individual database provided by the National Insurance Agency, this is not possible.

3. A Broad Empirical Picture

A first question refers to the most relevant geographical domain when analyzing local social interaction. Municipalities may be too large for this purpose. We have therefore chosen so-called SAMS (Small Area for Market Statistics), which simply will be called “neighborhoods”. The aim of the definition of such areas is to provide reasonably homogenous districts based on geographical proximity among inhabitants and on similarity in

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4 Skogman Thoursie (2004) found that such absence increased by 16 percent among men as compared to women in connection with the World Championships in cross-country skiing in 1987, and by 6.6 percent in connection with the Winter Olympics in 1988. Similarly, Persson (2005) found that sickness absence among men increased by 41 percent as compared to women in connection with the 2002 World Championship in football. All three studies used a difference-in-difference methodology with females as a control group.

5 The reason is that the individual employers pay for shorter spells, and that data on such spells are not systematically collected. The total average number of sick days for which sickness pay was claimed was about 25 per during the investigated period.

6 We have excluded individuals younger than 18 and older than 64 years as well as individuals in military service and the self-employed.

7 See Statistics Sweden (2005) for a detailed description of this geographical specification.
There are 9,003 SAMS areas in our database. After excluding some individuals outside the labor force from the data set, as mentioned in footnote 2, the average population of the SAMS is 468 persons.

Let $S_{i,n}$ denote the number of sick days of individual $i$, living in neighborhood $n$. The average number of sick days per individual in a given neighborhood then is

$$\bar{S}_n = \frac{\sum_{i=1}^{N_n} S_{i,n}}{N_n}, \quad n = 1, \ldots, 9003,$$

where $N_n$ is the number of individuals in neighborhood $n$.

The average number of sick days (above 14 days) in the data is 17; the wide dispersion in neighborhood averages is reflected in a standard deviation of 5.4 and a range of 330 days per year. How can this wide variation be explained?

The first question is whether the local variation can simply be explained by observable socio-economic factors. To answer this question, we run a multivariate regression where each individual is characterized by three types of socio-economic variables: individual characteristics (such as age and education), workplace characteristics (industry and plant size), and neighborhood characteristics (such as urban/rural, local unemployment, and a local health variable. We have chosen explanatory variables that in different studies have turned out to be important for sickness absence. A full list of the socio-economic variables is given in the Appendix.

To investigate the role of socio-economic variables, we run a simple OLS regression of the form

$$S_{i,n} = \alpha + X_{i,n}b + e_{i,n},$$

where $X_{i,n}$ denotes the vector of such variables. The large number of observations makes it possible to apply many explanatory variables without running into problems with the degrees

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8 In large municipalities, the SAMS district could be characterized as an area with similar housing characteristics within the same church district (parish). In smaller municipalities or rural areas, the SAMS districts are based on the election districts. The SAMS geographical specification does not have any administrative usage. It has previously been used primarily by Statistics Sweden in commissioned research on urban and infrastructure planning as well as medical research. The division departs from the national housing register.

9 We have not included income in the $X$ vector. The reason is that reported income is affected by the individual’s sickness absence; including it among the explanatory variables would thus cause a bias in the $\beta$ estimates. Several of our explanatory variables are, however, correlated with income – for instance, age, education, gender, and industry.
of freedom. By using dummy variables, we obtain a highly flexible specification of the regression equation. For instance, age is not represented by a linear function (or even a polynomial) of the individual’s age, but by 46 dummy variables, one for each age group between 18 and 64. In total, we use 166 variables.

In addition to age, gender and education, it turns out that health and unemployment are the most important socio-economic explanations of variations in sickness absence across geographical areas. We then represent health by regional life expectancy, which varies by about two years between counties with the highest and the shortest life expectancy. This explains differences in sickness absence up to approximately two days per year across neighborhoods. The covariation of sick absence and local unemployment is more complex, since the relation seems to be non-linear, with a positive (partial) relation at low unemployment and a negative relation at high – the latter possibly reflecting a so-called disciplinary effect in the efficiency-wage literature.

However, including unemployment in the regression equation (1) creates a problem when analyzing the role of social norms. One reason is that some individuals may choose sickness benefits rather than unemployment benefits since the former are often more generous and perhaps also less stigmatizing. Another reason is that unemployment in itself may reflect the influence of social norms concerning benefit dependency in general: higher unemployment may reduce the stigma of living on benefits in general. Therefore, including unemployment among the explanatory variables in the \( X \) vector could mean that one is unknowingly including social norms in the \( X \) vector; this would tend to bias our estimates of the influence of social norms downwards. In the empirical analysis reported below, we have included unemployment as an explanatory variable, but the results are basically the same if unemployment is excluded.

As expected, running a regression on (1) has a rather low power in explaining individual behavior, which is mainly determined by idiosyncratic factors (\( R^2 = 0.0354 \)). What is more

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10 Since we do not have life expectancy data for municipalities, we have used data for the county where each neighborhood is located.

11 In our data, we have defined local unemployment as the unemployment incidence, i.e., the percentage of the inhabitants in neighborhood \( n \) who received unemployment benefits at least once during the year. This variable thus takes the range 0 to 100 percent.

12 For instance, Åberg, Hedström & Kolm (2006) argue that local variations in unemployment in Sweden partly depends on differences in local social norms towards living on unemployment benefits.
surprising is that the $X$ vector explains so little of the variation of average absence across neighborhoods. Indeed, the variation is nearly as large after controlling for 166 variables as in the raw data. Defining the average residual in neighborhood $n$ as

$$\bar{e}_n = \frac{\sum_{i=1}^{N_n} e_{in}}{N_n}, \quad n = 1, ..., 9003,$$

the standard deviation of the distribution of residual averages is 4.6, as compared 5.4 in the raw data (the range is about the same). Thus, even after controlling for a large number of socio-economic factors, there is still a huge unexplained variation in average sickness absence across municipalities.

The next question is whether the distribution of average residuals is purely random. We test this by allowing for fixed neighborhood effects by replacing the intercept $\alpha$ in equation (1) by one separate $\alpha_n$ for each neighborhood. The relevant test statistic for systematic neighborhood effects is $F = 5.880$. Hence, the hypothesis of no neighborhood effects is rejected at the one-percent level of significance (see, for instance, Greene, 2003, chapter 13, equation 13-9).

Of course, the large dispersion of average residuals is not necessarily a sign of social interaction among neighbors. Instead, the dispersion might reflect unobservable local factors, such as the climate or local environmental problems, not reflected in the $X$ vector but nevertheless affecting sickness absence. There is, however, no reason why such factors would influence changes over time in sickness absence. We therefore control for the influence of such factors by looking at changes rather than levels of sickness absence:

$$DS_m = \alpha + \text{X}'_m b + e_m. \quad (2)$$

Just as in the case of levels (1), the average residuals in changes across neighborhoods vary systematically, i.e., in a non-random fashion ($F = 1.559$). Thus, there are significant systematic neighborhood factors behind the local variation in sickness absence, for changes as well as for levels.

4. Modeling Social Interaction

Note that since local life expectancy is included in the $X$ vector, such an omitted unobservable variable has to affect health, but at the same time be unrelated to life expectancy.
One way in which social interaction, including social norms, has been analyzed in the literature is to assume that the individual’s behavior is influenced by the average behavior of adjacent individuals. We follow this tradition in the present paper. Denoting the average sick absence in neighborhood \( n \) by \( S_n \), we formalize this assumption as

\[
S_i^n = a + X_i^n b + gS_n + e_i^n. \tag{3}
\]

The question, then, is whether \( g \) is significantly different from zero. An unsophisticated estimation of (3) yields the coefficient \( \hat{g} = 1.101 \), which is significant at the one percent level. It is well known, however, that running such a regression tends to give a biased estimate of \( g \) because of the so-called reflection problem (Manski, 2000): on average, an individual’s behavior is tautologically related to the average individual’s behavior. Indeed, the coefficient would tend to be biased towards unity. (The reflection problem is, of course, related to Haavelmo’s general econometric simultaneity problem.) If the \( X_i^n \) vector were complete, in the sense that it included all variables that influence the absence behavior of individual \( i \) beside the influence of social interaction, then there would be no reflection problem. Equation (3) could then be easily estimated by OLS, and \( \hat{g} \) would be an unbiased estimate of the effects of group behavior on individual behavior. In reality, the \( X_i^n \) is never complete in this sense; there are many unobservable factors that affect individual behavior, and therefore we have to find a way to deal with the reflection problem.

A very commonly used method to separate out the effects of unobserved heterogeneity from a regression is to estimate fixed individual effects. In our analysis, however, this procedure does not solve the heterogeneity the results in the reflection problem. To see this, let us eliminate the individual fixed effects by calculating differences on both sides of equation (3), i.e.,

\[
D_S_{ikt} = b DX_{ikt} + \Phi D\bar{S}_{kt} + n_{ikt}.
\]

Since this model states that the individual’s change in work absence is related to the change in average absence in the individual’s neighborhood, it obviously suffers from the same reflection problem as our models expressed on levels. Another limitation of trying to achieve
identification through differences is that the theory of social interaction applies to equilibrium levels rather than to changes in behavior.

A further possibility would be to calculate differences on the left-hand side only. This would lead us to a different type of model, which we will discuss more thoroughly in terms of the diffusion of social norms in Section 4.2 below.

To deal with the reflection problem, we use the four approaches mentioned in the Introduction. More specifically, we rely on the difference in absence behavior of public- and private-sector employees, the influence of the behavior of natives on immigrants, the interaction between neighborhood and workplace effects, and the diffusion of absence behavior across individuals. Within each of these four approaches, we use alternative model specifications and estimation techniques. As we shall see, each one of these approaches has specific weaknesses – but taken together, they give accumulated evidence on the importance of social norms.

4.1 Public-sector vs. private-sector employees: an IV approach
As a first approach to identifying the influence of social norms on sickness absence we exploit the fact that public-sector employees have systematically higher sickness absence than private-sector employees. The basic identifying assumption is that individuals with specific sick-behavior characteristics do not choose to settle down in communities on the basis of the proportion between the public and the private sector in these communities – or visa versa.

We apply an instrumental-variable (IV) approach to predict the average sickness absence in a neighborhood by the share of the inhabitants working in the public sector. For this purpose, we define the variable $Z_n$ as the proportion of public-sector employees (central plus local government) in neighborhood $n$. We use $Z_n$ as an instrument in the 2SLS estimation of the system

$$\begin{align*}
\bar{S}_n &= a + X'_n \beta + cZ_n + e_n \\
S'^{priv}_n &= a + X'_n \beta + g\hat{S}_n + e_n,
\end{align*}$$

14 The average number of days of sickness absence in our data set (spells above 14 days) by sectors in 2001 were: private-sector employees 12.2; central government employees 15.4; municipal employees 20.3.
where $S_{in}^{priv}$ is the sickness absence among private-sector employees. Conversely, we use $1 - Z_n$ as a regressor in the first-stage equation in (4'), and we enter $S_{in}^{publ}$ (i.e., absence among public-sector employees) as the dependent variable in the second equation:

$$
\bar{S}_n = a + X_n b + c(1 - Z_n) + \epsilon_n
$$

$$
S_{in}^{publ} = a + X_n b + g\bar{S}_n + \epsilon_n.
$$

(4')

The resulting estimates of $g$ are shown in the fifth column of Table 1.

Table 1: Estimates of $m$ and $g$ in equations (4) and (5)

<table>
<thead>
<tr>
<th>Population</th>
<th>Number of observations</th>
<th>Regressor</th>
<th>$\hat{g}$ in eq. (4)</th>
<th>$\hat{m}$ in eq. (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All who work in private sector</td>
<td>2,173,260</td>
<td>Share of population in neighborhood $k$ that work in public sector ($Z_k$)</td>
<td>0.639*** (0.095)</td>
<td>2.971*** (0.446)</td>
</tr>
<tr>
<td>All who work in public sector</td>
<td>1,443,385</td>
<td>Share of population in neighborhood $k$ that work in private sector ($1 - Z_k$)</td>
<td>1.756*** (0.135)</td>
<td>-8.381*** (0.626)</td>
</tr>
</tbody>
</table>

*** indicates significance at the 1 percent level.
In the case of (4), which refers to private-sector employees, we obtain the estimate $g = 0.639$. This means that if the average number of sick days in a neighborhood increases by one day, a random private-sector individual would increase his number of sick days by 0.639 days. If we instead estimate $(4')$ for the population of public-sector employees, using $1 - Z_d$ as an instrument, the corresponding $g$ estimate is 1.756.

Both estimates look quite high, in particular the second one. Indeed, a coefficient above unity would generate an explosive development in a long term perspective, and it could presumably only exist for a limited period of time. Indeed, the estimated coefficient might be biased upward because of selection mechanisms, which could violate our basic identifying assumption that there is no tendency for employees in the private sector with high (low) propensity to live on sickness benefits to settle down in areas with a high (small) proportion of public sector employees. There are, in fact, conceivable selection mechanisms that might violate this identifying assumption. For instance, it is possible that individuals with relatively generous interpretation of the rights to live on government-provided benefits chose to live in areas with a large proportion of public-sector employees. One conceivable mechanism could be that individuals with leftist political sympathies hold such views, and they also tend to settle down in areas with similar political sympathies, which they are likely to find in areas with a large fraction of public-sector employees. Another example of selection might be that individuals with strong career ambitions and expectations of rising income (and hence also low propensity to live on sickness benefits) tend to settle down in neighborhoods with large fraction private-sector employees with similar ambitions. In our analysis, such selection bias could in both cases mistakenly be interpreted as a causal effect of group behavior on individual behavior. Other mechanisms with similar selection results could perhaps also be conceived. If these self-selections had occurred according to some observable variables, these variables could simply be included in the $X$ vector, and the problem of self-selection could thus be handled. However, we can not expect this to be generally the case.

A more direct way of estimating the social interaction between public and private employees is to apply an OLS to the reduced form

$$S_{priv} = a + X_{priv} \beta + Z_d \gamma + \epsilon_m.$$ (5)
In other words, we simply ask whether private-sector employees tend to be more absent from work if they have many neighbors who work in the public sector. Here, the estimate of $m$ is expected to be positive.\textsuperscript{15} Similarly, we ask whether public-sector employees tend to be less absent from work if they live in neighborhoods where there are many private-sector employees:

$$S_{m}^{\text{publ}} = a + X_{m} b + m (1 + Z_{n}) e_{m},$$  \hspace{1cm} (5')

where we would expect a negative sign of $m$.

The results are shown in the last column of Table 1. As expected, a higher share of public-sector employees in a neighborhood increases sickness absence among private-sector employees in that neighborhood. The number 2.971 in the fifth column of the table means that if the share of public-sector employees increases by 10 percentage points, sickness absence among privately employed increases by approximately 0.297 days per year. Similarly, if the share of private employees in a neighborhood increases by 10 percentage points, the number of sick days among public-sector employees in that neighborhood falls by 0.838 days per year.

Although self-selection might bias the figures upward both in the IV and the reduced form OLS regressions, another factor tends to generate an underestimation of the effects of social norms. We refer to the fact that our model specifications exploit only the difference in behavior between public and private sector employees, and hence that it only reflect the transmission of social norms between employees in the public and the private sector. Hence, it does not reflect all types of social interaction of sickness absence behavior. In particular, interaction within the group of public-sector and private-sector employees is not covered.

Because of these various limitations and complications of the analysis in this section, it is important to try other approaches to identify indicators of the role of local social norms for sick-absence behavior.

\textsuperscript{15} Note that the estimation of $m$ does not provide an estimate of the influence of average behavior on the individuals (like $g$ in equation (4)); it is just an indication of social interaction.
4.2 A Diffusion Model

Another empirical strategy to find evidence of the operation of social norms is to apply diffusion models, traditionally used in epidemiology for studying the spread of contagious diseases and, in economics, to analyze geographical dissemination of technological innovations. In general terms, such models may be written

$$D\bar{S}_n = f(\bar{S}_n),$$

indicating that the change in the average sick absence in neighborhood $n$ depends on the level of absence in that neighborhood. Depending on the shape of the function $f(.)$, we can distinguish between a so-called *exogenous* diffusion model, for which $f$ is monotonically decreasing in $\bar{S}_n$, and an *endogenous* diffusion model, for which $f$ has an “inverse U shape”.

According to the exogenous diffusion model, the number of sick absence days in a neighborhood does *not* depend on local social interaction among individuals – as a result of persons absent from work meet non-absent ones – but on the influence of, for instance, national mass media reaching the entire population. Thus, if absence is already very high among in a certain neighborhood, the marginal utility of a further increase for a given individual is relatively small, and we would expect that the likelihood of a further increase in absence is relatively small in such a neighborhood. The analogy in the case of infectious diseases is that the further spread of a disease will slow down when the number of non-infected individuals shrinks. The exogenous diffusion model may therefore be written

$$D\bar{S}_n = h + \hat{k} \ (365 - \bar{S}_{n,t-1}) + \epsilon_n,$$  \hspace{1cm} (6)

where we would expect $\hat{k} < 0$.

By contrast, the *endogenous* diffusion model presumes that norms, diseases and innovations are spread via social interaction. In this case, an individual is more likely to increase his sickness absence if he encounters many individuals who live on sickness benefits in his neighborhood. This means that the endogenous diffusion model may be written
\[ D\bar{S}_n = h + k \left( 365 - \bar{S}_{n,t-1} \right) \bar{S}_{n,t-1} + e_n, \quad (6') \]

where we expect \( \hat{k} < 0 \).

Table 2: Results from four different diffusion models. Dependent variable: change in average neighbourhood utilization of the sickpay insurance.

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_{65} - \bar{S}_{n,t-1} )</td>
<td>0.114*** (0.008)</td>
<td>-</td>
</tr>
<tr>
<td>( \beta_{65} - \bar{S}<em>{n,t-1} \bar{S}</em>{n,t-1}/1000 )</td>
<td>0.348*** (0.022)</td>
<td>-</td>
</tr>
<tr>
<td>( \bar{S}_{n,t-1} )</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( \bar{S}_{n,t-1}^2 )</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>X vector included</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R^2 )</td>
<td>0.0063</td>
<td>0.0063</td>
<td>0.0063</td>
</tr>
<tr>
<td>Number of observations</td>
<td>4,174,180</td>
<td>4,174,180</td>
<td>4,174,180</td>
</tr>
</tbody>
</table>

Column 1 and 2 in Table 2 show the results from the estimation of model (6) and (6’), respectively. In both estimations we also include the vector of observable characteristics described in Section 2. The results show a significantly negative coefficient estimate for the exogenous model (6) and a significantly positive one for the endogenous model (6’). Since the exogenous model is only interpretable with a positive sign, it means that it is rejected by the data. The positive coefficient estimate for the endogenous model (6’) is, however, interpretable and the model specification can be maintained.

The functional form of the endogenous diffusion model (6’) is very restrictive. The entire relation between the local level of the share of utilization of the sickpay insurance and the change in this level is described with one parameter. A very similar, but more flexible, alternative, which allows for the hump-shaped relation implicit in model (6’), is a quadratic function in the local level of utilization of the sickpay insurance, i.e.,
Column 3 in Table 2 shows the results from the flexible quadratic specification (6’’). Since the coefficient for the quadratic component turned out significant, we are able to reject the linear specification. The negative coefficient estimate for the quadratic term suggests a similar form as the one implied by the endogenous diffusion model (6’), i.e., it confirms an endogenous diffusion process.

One objection to interpreting our results as reflecting social interaction could be that the estimated diffusion model simply reflects the transmission of infectious diseases, e.g., flu. It is well known, however, that infectious diseases constitute a very limited part of the utilization of the sickpay insurance program in Sweden; instead, the bulk of absence days refers mainly to asserted muscular-sclerotic problems and mild mental problems, both of which are difficult to disprove by medical examination.\footnote{See e.g. Alexanderson and Norlund (2004, p. 21).} This point is particularly for spells longer than 14 days, which are the only ones recorded in our data. We will therefore interpret the diffusion process as an indicator of social transmission of norms concerning the utilization of the sickpay insurance program, i.e., as social interaction.

### 4.3 Immigrants and Natives

An alternative way of investigating the influence of social norms, without running into the reflection problem, is to study the behavior of immigrants. Our hypothesis is that immigrants who settle down in a given neighborhood in Sweden adjust their behavior to the behavior of the native population in that neighborhood. To test this hypothesis, we estimate the following equation:

$$S^m_n = a + bX^m_i + g\bar{S}_n + e_n. \quad (7)$$

Here, $S^m_n$ is the number of sick days of immigrant $i$ in neighborhood $n$, while $\bar{S}_n$ is the average number of sick days among native Swedes in neighborhood $n$. Note that the $S$ on the left-hand side refers to the behavior of a different group of people than the $S$ on the right-hand side. As a result, there is no reflection problem in this case – although there may be a
selection problem (see below).\textsuperscript{17} We thus can rely on OLS, rather than 2SLS, estimates. The identifying assumption in this regression is that there is no tendency – in addition to what is reflected in the the $X$ vector – among immigrants with a high propensity to be absent to settle down in neighborhoods where absence among native Swedes are particularly high. The results of estimating equation (7) are reported in Table 3.

\textsuperscript{17} In principle, one could run a 2SLS regression in this case as well, using the instrument $Z_{in}$, the fraction of the population in neighborhood $n$ that are native Swedes. This approach presupposes, however, that there are systematic absence behavior between immigrants and native Swedes (just like the differences between public and private sector employees in Section 3.1). Such a difference does not seem to exist, however.
Table 3: Estimation results for immigrants

<table>
<thead>
<tr>
<th>Region of origin</th>
<th>All immigrants</th>
<th>Recent immigrants</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of observations</td>
<td>Estimate of $\sigma$ in equation (6)</td>
</tr>
<tr>
<td>All regions</td>
<td>584,851</td>
<td>0.337*** (0.019)</td>
</tr>
<tr>
<td>Nordic countries</td>
<td>156,465</td>
<td>0.689*** (0.041)</td>
</tr>
<tr>
<td>EU (except Nordic countries)</td>
<td>55,685</td>
<td>0.136*** (0.058)</td>
</tr>
<tr>
<td>Europe (except EU)</td>
<td>129,462</td>
<td>0.203*** (0.043)</td>
</tr>
<tr>
<td>Africa</td>
<td>37,421</td>
<td>0.192*** (0.064)</td>
</tr>
<tr>
<td>North America</td>
<td>15,047</td>
<td>0.249*** (0.086)</td>
</tr>
<tr>
<td>Latin America</td>
<td>31,107</td>
<td>0.199*** (0.085)</td>
</tr>
<tr>
<td>Asia</td>
<td>153,725</td>
<td>0.163*** (0.034)</td>
</tr>
<tr>
<td>Oceania</td>
<td>2,380</td>
<td>0.007 (0.154)</td>
</tr>
<tr>
<td>Former Soviet Union</td>
<td>3,385</td>
<td>0.287 (0.289)</td>
</tr>
<tr>
<td>N/A</td>
<td>174</td>
<td>-0.547 (0.535)</td>
</tr>
</tbody>
</table>
According to these estimates, sickness absence among immigrants is 0.337 days higher in a neighborhood where absence among Swedes is one day higher than in another neighborhood. The estimate is highly significant. We have also disaggregated this average for ethnic subgroups. For immigrants from other Nordic countries, the estimated coefficient is largest, namely 0.689. It is tempting to interpret this large number as the result of a particularly strong social interaction between native Swedes and immigrants from other Nordic countries.

Could these results depend on selection rather than on social interaction? In other words, could there be mechanisms by which immigrants with a high propensity for sickness absence are selected into areas where the natives have a similar propensity? When answering this question, it should be noticed that immigrants in Sweden, who usually are refugees, often are geographically allocated by the authorities. It is conceivable that the authorities unintentionally allocate immigrants to areas where the absence rates are particularly high among the Swedes. One reason might be that immigrants are often allocated to areas with empty apartments, which usually means areas with low employment prospects and perhaps relatively high rates of sickness absence among natives. There is, however, no reason to assume that the authorities allocate immigrants with a particularly high absence propensity to such areas, and other immigrants to more prosperous areas.

Self-selection may be a more serious problem than administrative selection. There are two types of self-selection involved here. Regardless of whether they originally were allocated to certain areas by the authorities or chose a particular area by themselves, they may subsequently move to other areas in the country. Is there a possibility that these movements violate our identifying assumption that immigrants with a high propensity to be absent do not settle down in areas where many Swedes are absent from work? For instance, it is possible that people with strong labor-market ambitions have a particularly strong tendency to leave areas with a weak labor market. This would mean that less ambitious immigrants would remain in areas with Swedes that also have modest labor market ambitions. If labor-market ambitions are correlated with the propensity to be absent, and this is not reflected in the $X$ vector, such a mechanism may create a selection bias in the regression. Taking this possibility seriously, we have run regressions confined to recent immigrants (arriving in Sweden during 1999-2002). The rationale for looking specifically at this group is that it takes time for individuals both to learn which areas suit them best, and how to move there. We would, therefore, expect that the problem of self-selection in our estimates is more limited for recent
immigrants than for immigrants in general. The estimates for this subgroup are shown in the last column of Table 2. They are also highly significant and do not differ much from the estimates for the entire group of immigrants. (For some groups the coefficients are higher, and for some groups lower). The selection bias may therefore not be a serious problem.

4.4 Strength of Networks within Neighborhoods and Workplaces

If social interaction on the neighborhood level influences individual work absence behavior it is likely that the effect is stronger if there are frequent social contacts between individuals, i.e., if there are strong networks in the neighborhood. This provides an additional possibility to identify the effect on individual behavior of the average level of work absence in the neighborhood. The social interaction is likely to be stronger if the individual meets others in more than one network – neighborhoods, workplaces, and groups with similar educational backgrounds or from the same industry.

We use two strategies for measuring the intensity in social interaction. First, we represent the intensity of social interaction by the share of people in the neighborhood who also work at the same workplace. If two persons meet both in their neighborhood and at their workplace, it is likely that they influence each other more than they would do otherwise. Alternatively, we represent the intensity of interaction by the share of individuals within the neighborhood who have the same education level and work in the same sector. In other words, we assume that social interaction increases by the neighborhood homogeneity: it is likely that the networks become stronger if they are more homogenous.

We use the following model for estimating the first interaction mechanism described above:

$$ S_{inw} = a + X_i b + g(CA_{inw}, \bar{S}_n) + \lambda_w + m_n + j CA_{inw} + \epsilon_{inw}, $$

(8)

where $w$ is a sub-index for workplace and $n$ for neighborhood. Here, $CA_{inw}$ measures the strength of the network facing individual $inw$, defined either as the fraction of workmates within the neighborhood, or as the fraction of persons with a similar education (and working in the same industry) in the neighborhood. $\lambda_w$ and $m_n$ are fixed effects for workplaces and

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18 In the cases where the coefficients are lower for recent immigrants than for the total stock of immigrants, this may reflect time lags in adjustment to local norms, rather than self-selection.
neighborhoods, respectively. This is basically the same analytical structure as the one used by Berton et al. (2000) when studying the interaction between language groups and neighborhoods when explaining the reliance on social assistance (“welfare” in U.S. terminology) among ethnic minorities in the United States.

An important feature of the specification in equation (8) is that the fixed workplace and neighborhood effects control for omitted variables on the workplace and neighborhood levels, respectively. As we described in the beginning of section 4, the so-called reflection problem precludes a direct estimate of the effect of the average work absence level in the individual’s reference group if individuals select according to some unobservable characteristics. In specification (8), however, the fixed effects control for the unobservables that may bias the estimation. Our identifying assumption is that it is no separate interaction between the neighborhood and workplace factors in equation (8).

In addition to the fixed effects, equation (8) includes the density (concentration) measure CA separately. This allows us to control for the possibility that the strength of the network in itself may be correlated with unobservable characteristics systematically related to the propensity to be absent from work.

It is likely that the workplace also has an important role in the formation of work norms. The analysis outlined in model (8) can be paralleled replacing the neighborhood with the workplace, i.e.,

\[ S_{mn} = a + X'B + \gamma(CA_{wn} \bar{S}_n) + I_m + m + \gamma CA_{wn} + \varepsilon_m. \]  

(9)

The only difference compared to the specification in equation (8) is that the measure of the network intensity in the neighborhood is replaced by the intensity at the workplace, and that the average work absence in the neighborhood is replaced by the absence at the work place. Again, we use two different measures of the network intensity. First, we use the share of individuals at the workplace living in the same neighborhood. Second, we use the share of individuals in the same education group at the workplace.
Table 4 shows the results from the OLS estimation of the models in equations (8) and (9). In addition to the variables shown in Table 4, we also include a vector of individual characteristics. These include dummy variables for each one-year age groups, gender and 7 educational levels. The network intensity variable only varies on the neighborhood/workplace level for the first measure of the network intensity, and the sector/education group level for our second measure. We therefore adjust the standard errors for clustering within these cells. For the neighborhood equation we use two education levels (compulsory and vocational schooling v/s secondary education and beyond) and two sectors (public and private). In the workplace equation the sector classification cancels out. In the lower panel of Table 4, we show the average and standard deviations for our different measures of network intensity. The models are estimated on data from the 2000 cross section.

Table 4: Estimates of $\vartheta$ from the model of interaction between neighborhoods and workplaces.

<table>
<thead>
<tr>
<th></th>
<th>Neighborhoods, equation (8)</th>
<th>Workplaces, equation (9)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Workplace interaction</td>
<td>Sector/education group interaction</td>
</tr>
<tr>
<td>$\hat{\vartheta}$</td>
<td>3.580*** (0.045)</td>
<td>2.808*** (0.042)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.016</td>
<td>0.015</td>
</tr>
<tr>
<td>Number of observations</td>
<td>2,554,849</td>
<td>2,554,849</td>
</tr>
<tr>
<td>$CA$</td>
<td>0.095</td>
<td>0.227</td>
</tr>
<tr>
<td>$\hat{CA}$</td>
<td>0.139</td>
<td>0.097</td>
</tr>
</tbody>
</table>

The first two columns in Table 4 show the results for neighborhoods. The estimates for the interactions are positive and highly significant for both measures of network intensity. The marginal effect of a change in the average work absence level ($\frac{\delta Y_i}{\delta \bar{Y}_n} = \vartheta CA_{nw}$) on the individual’s work absence, using the average network concentration level, suggests an effect

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19 Note that the vector $X_i$ in (8) and (9) is a subset of the previously used vector. The neighborhood and workplace variables vector become redundant because of the neighborhood and workplace fixed effects in (8) and (9).
around 0.34, which is lower than our IV estimates for both public- and private-sector employees (see Table 1). The last two columns in Table 4 show the results for workplaces. Although the effects are relatively small, they are positive and highly significant. We can, again, reject the hypothesis of no social interaction.

5. Conclusions

There are large variations in sickness absence, across time and across geographical areas. These variations are difficult to explain by observable socio-economic factors and the rules of the sickness insurance system. Could the absence patterns be explained by variations in social norms? Since social norms occur through interaction between individuals, it is natural to look at sickness absence in neighborhoods; the aim is then to capture the dissemination of local norms concerning the utilization of the sickness insurance system.

We have used several different approaches to identify such social interaction. As mentioned in the Introduction, the main challenge in this type of study is to disentangle the causal influence (of group behavior on individual behavior) from simple correlation (due to sorting of individuals according to various unobservable characteristics related to sickness absence). In some approaches, we have tried to find indications that local social norms actually operate – while in other approaches we have tried to quantify the effects of the norms.

For instance, we find evidence that absence behavior among public-sector employees affect the behavior of private-sector employees in the same neighborhood, and vice versa. We have also found that the intensity of networks play a significant role. One indication is that people who know each other from several arenas seem to affect each other more than others. For instance, people who are both neighbors and workmates, or who are not only neighbors but also share the same educational background and work in the same sector, are more affected by local norms. Finally, a diffusion model also suggests that norms concerning work absence are transmitted through local social interaction.
References


Lindbeck, Assar and Mats Persson, 2006, A Model of Income Insurance and Social Norms, CESifo working paper No. XXX.


Modig, Arna and Kristina Broberg, 2002, “Är det OK att sjukskriva sig om man inte är sjuk?” (Is it OK to be on sick leave if you are not sick?), memorandum T22785, TEMO, Stockholm.


Refina Information AB, 2005, “Kunskaps- och attitydstudie avs. sjukförsäkringen” (Knowledge and attitude study concerning sick-pay insurance), mimeo, Stockholm.


Appendix: Explanatory variables in the $X$ vector

<table>
<thead>
<tr>
<th>For the individual</th>
<th>age</th>
<th>(all ages from 18 to 64, one dummy for each age, i.e., 46 dummies)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>education</td>
<td>(seven levels, one dummy for each, i.e., six dummies)</td>
</tr>
<tr>
<td></td>
<td>gender</td>
<td>(one dummy)</td>
</tr>
<tr>
<td></td>
<td>marital status</td>
<td>(single, married/cohabiting or divorced, i.e., two dummies)</td>
</tr>
<tr>
<td></td>
<td>having children aged 3 or younger</td>
<td>(one dummy)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>For the workplace:</th>
<th>industry</th>
<th>(60 industries, i.e., 59 dummies)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>sector</td>
<td>(central government authority, state-owned enterprise, local government authority, local government-owned enterprise, private firm, etc. 11 sectors, i.e., 10 dummies)*</td>
</tr>
<tr>
<td></td>
<td>size of workplace</td>
<td>(21 dummies: 1 employee, 2-10, 11-20, 21-30, …, 91-100, 101-200, 201-300, …, 901-1000, 1001-9999 employees)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>For the neighborhood:</th>
<th>town or countryside</th>
<th>(one dummy)</th>
</tr>
</thead>
<tbody>
<tr>
<td>local unemployment</td>
<td>(expressed by the incidence of unemployment, i.e., the fraction of the labor force in the area that has at least once received unemployment compensation during the year. 19 dummy variables, one for each 5-percent interval)</td>
<td></td>
</tr>
</tbody>
</table>

* The distinction between industry and sector is that the former refers to the type of product or service produced, while the latter refers to ownership characteristics