The Spirit of the Welfare State? Adaptation in the Demand for Social Insurance

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Abstract

Young generations demand substantially more social insurance than older generations, although program rules have been constant for decades. I postulate a model where the utility of taking up social insurance benefits depends on the past behavior of older generations. The model is estimated with individual panel data. The intertemporal mechanism estimated can account for half of the younger generations' higher demand for social insurance benefits. Instrumenting for older generations' behavior using mortality rates reveals an even stronger influence of reference group behavior on individual demand for benefits. The analysis suggests that behavioral responses to the provision of welfare state benefits estimated by natural experiments are likely to strongly underestimate the true long-run elasticities relevant for the fiscal sustainability of the welfare state.

JEL codes: H31, I18, J22, Z13

Key words: social insurance, adaptation, role models, sick leave

1 Introduction

Do social insurance programs have long-run effects on behavior? If so, what are the magnitudes of these effects and what mechanisms could explain them? In spite of a large theoretical literature on the long-run effects of policy, few empirical studies address these questions. I show that these long-run effects are quantitatively important, implying stark consequences for policy design and the

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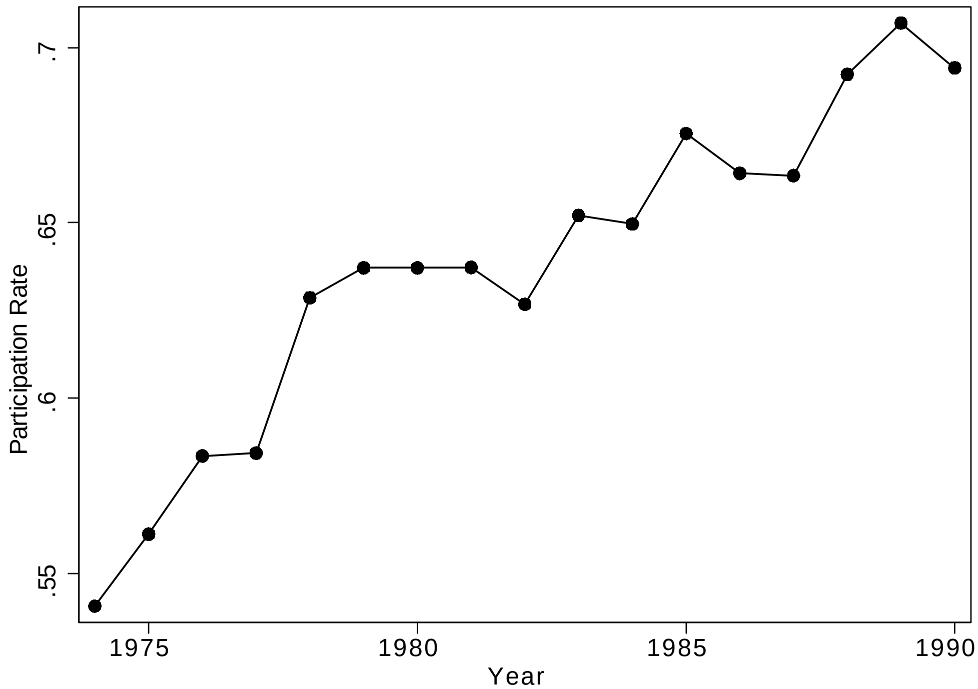

Figure 1: Sick Leave Participation Rate, 1974-1990. Sample: Labor force participants, ages 22-60.

fiscal sustainability of welfare state programs. The fiscal sustainability of programs cannot be assessed by the short-run effects the treatment effect literature has focused on.

I study behavior during the decades following the expansion of the welfare state in Sweden. I focus on the take up of sick leave benefits, which replace lost earnings due to illness or injury.[1] The average take up rate was 54 percent in 1974 and 69 percent in 1990, as seen in Figure 1. Take up increased by almost one percentage point per year during a period when program generosity was constant.

Plotting the behavior by birth cohort presents an even clearer pattern, as

[1] Take up is defined as receiving some (that is, at least one day of) benefits during the year.

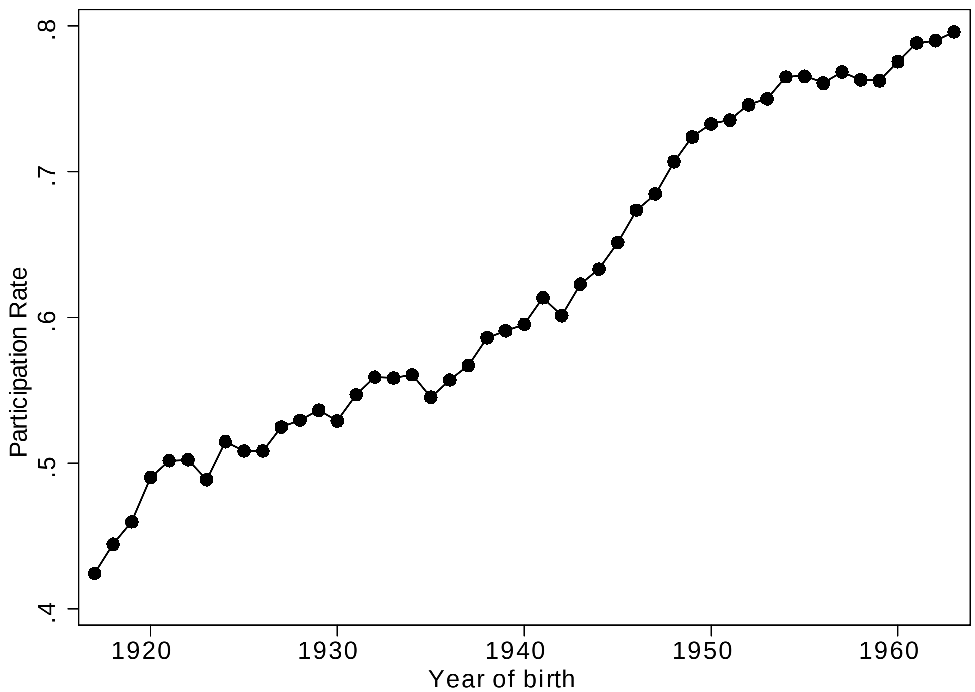

Figure 2: Sick Leave Participation Rate by Cohort. Sample: Labor force participants, ages 22-60. Years 1974-1990.

seen in Figure 2. The generation born in 1919 has an average take up rate of 45 percent, that is, they use sick leave benefits a bit less than half the years they are in the labor force. For the generation born 1960 the take up rate is almost 80 percent.[2] Each younger birth cohort has a take up rate that is almost 1 percentage point higher than those born one year earlier. Behavior has adapted significantly in the face of constant institutions, as seen in Figures 1 and 2, consistent with theories about changing work norms in response to the welfare state.

Analyzing sick leave take up in Sweden has one distinct advantage compared to other behavior. The take up decision is completely at the individual's

[2] Older generations are observed later in their life cycle when their health may be worse, so higher take up rates might have been expected for older generations compared to the young.

discretion. Behavior is determined by demand, unlike other programs such as unemployment benefits whose use is also determined by supply side factors.

My empirical analysis proceeds in two parts. First, I account for a large number of factors that could influence benefit take up and potentially explain the cohort trend seen in Figure 2; this trend persists. Second, I write down a model of work norm transmission and estimate a mechanism that could explain the cohort trend. To make a stronger case for a causal relationship I use instrumental variables, to address concerns that health trends drive the results.

Models study how institutions and behavior interact in the long run, in particular, how work norms shape benefit use. The mechanism I estimate is closely related to the evolution of work norms in Lindbeck, Nyberg, and Weibull (2003).[3] Doepke and Zilibotti (2008) model how work norms paved the way for a capitalist society. I study how these same work norms may respond in the long run to the introduction of the welfare state. Work norms are non-cognitive skills that may capture persistence and patience that the recent human capital literature has studied, see for example Almlund et al (2011). My analysis sheds light on how these skills are formed across generations and time.[4]

I allow for the benefit up take to depend on the sick leave behavior of peers, hence the behavior of slightly older role models can influence the individual's own decision.[5] The model is estimated using individual panel data, applying both pooled and within estimators. I account for non-linear time effects to rule out secular trends in behavior. The estimated coefficients indicate that the model could account for up to half of the cohort trend in Figure 2.

To make a stronger case for a causal effect of role model behavior on individual sick leave take up I use mortality rates as an instrument. Mortality rates capture health shocks that also affect sick leave. I find a strong reference group influence on individual sick leave behavior using both variation across

[3] Bisin and Verdier (2004) model work norms in the welfare state.

[4] Evidence on the intergenerational transmission from attitudes towards benefits use to general altruistic attitudes is prestented in Ljunge (2012a).

[5] The reference group influence may be interpreted as a psychic cost that captures, internal or external, stigma or some other effect that is captured by the reference group's behavior such as social learning or health consciousness.

individuals as well as within individuals over the life cycle. Results are robust to controlling for the mortality rates in the individual's own cohort, lending some plausibility to the identifying assumption that the mortality rates of older cohorts in the past has no direct influence on the individual's current sick leave take up.

The paper makes three contributions. First, I document large differences in sick leave behavior across cohorts, differences that can't be explained by observable factors. Second, I estimate a model that can explain half of the increase in benefit use across generations. Third, I make a compelling case that the estimated mechanism represents a causal relationship. Quantifying the size of the increased demand for social insurance and estimating a specific mechanism through which this adjustment takes place is an empirical question that, to my knowledge, I am the first to address.

The paper complements anthropological studies on sick leave in Sweden like Frykman and Hansen (2005, 2009) who find a generational divide in attitudes towards work and benefits use. I present unique quantitative evidence on how individuals adapt to institutions over time and across generations. The estimated dynamic model differs from the previous cultural transmission literature that has focused on determinants of different equilibria, but largely ignored the analysis of the path towards a new equilibrium.[6] The analysis is fundamentally distinct from the social interactions literature and from studies of the persistent effects of institutions in that both literatures are based on cross-sectional differences.[7] I study intertemporal differences, across generations and within life cycles, to examine how individuals adapt to social conditions. The treatment effect literature has focused on short-run evaluations of policy changes, which certainly are important questions, but at the expense of considering long-run effects that might dwarf the short-run responses.

The paper is organized as follows. The next section discusses the related

[6] See for example Guiso, Sapienza, and Zingales (2008) and Tabellini (2010), as well as the handbook chapter by Bisin and Verdier (2010).

[7] Studies of the influence of culture using immigrants, surveyed in Fernandez (2010), have a similar focus on cross-sectional differences.

literature. The third section describes the sick leave program, followed by the data description. Section 5 examines the cohort trend by accounting for individual characteristics. In the sixth section I develop the empirical model and the empirical results are presented. Section 7 concludes.

2 Related Literature

The study of long term adjustments in demand for social insurance, where individual behavior is followed across decades, complements several existing literatures. The effect of norms on labor supply (or benefit up take) has been studied both theoretically and empirically. The model I develop is most closely related to Lindbeck, Nyberg, and Weibull (2003) in how individual heterogeneity and the non-monetary cost are modeled, but it is also close to Lindbeck, Nyberg, and Weibull (1999). Doepke and Zilibotti (2008) study how work norms promoted capitalism, while I study how work norms may be affected by welfare state arrangements. The interplay between work norms and the welfare state have been modelled by Bisin and Verdier (2004), building on Bisin and Verdier's (2001) cultural transmission model, as well as Lindbeck and Nyberg (2006) who both focus on formation of norms in the family. I examine the influence of role models across generations rather than the link between parents and children. The analysis is also related to the dynamics of the welfare state in Hassler, Mora, Storesletten, and Zilibotti (2003). Their model implies sharp changes in behavior and policy. I present evidence of dynamics in individual behavior gradually over time during a period without sharp policy changes.

Fogli and Veldkamp (2011) study the evolution of female labor force participation. They write down a model of social learning similar to Fernandez (2011). The model is calibrated and the predictions of the model are close to the observed trends. Their emphasis on a model consistent with the data, without claims to a causal mechanism, is different from this paper's focus on examining a causal mechanism to explain the cohort trend.

There is a growing literature on the impact of beliefs or culture on economic outcomes and the paper is closely related to studies of how institutions and policy interact with beliefs.[8] The question I analyze is similar to studies on how institutional arrangements affect norms, like the effect of Communism on attitudes towards redistribution studied in Alesina and Fuchs-Schündeln (2007). I study how exposure to welfare state programs affects demand for social insurance, where different generations are treated differentially with respect to welfare state exposure. This exposure may affect norms regarding claiming government benefits, which in turn could affect demand for benefits. Changes in such norms may affect economic outcomes. Aghion, Algan, Cahuc, and Shleifer (2010) argue that trust affects regulation, based on a cross-country analysis. Individual panel data allow a much richer analysis with respect to the intertemporal adaptation and more detailed controls, including fixed individual characteristics, where the related literature to a large extent rely on country level variation.

Social interactions is a related literature, but distinct from the intertemporal analysis. That literature focuses on cross-sectional or spatial mechanisms, for example a contemporaneous effect of benefit up take in your reference group on your behavior. The effects of social interactions in the take up of welfare benefits have been studied empirically by Bertrand, Luttmer, and Mullainathan (2000) and Edin, Fredriksson, and Åslund (2003). Hesselius, Johansson, and Vikström (2009) find peer effects in sick leave in Sweden using a local policy change that lasted 6 months. Their focus is hence on the immediate effect across people, while I study long-run effects over the life cycle. Lindbeck, Palme, and Persson (2008) study peer effects in long term sick leave in Sweden, and they use several approaches to argue for peer effects. Their focus on longer sick leave spells measures a very different behavioral margin, incorporating both demand and supply effects, compared to the discretionary individual decision to demand sick leave I study. Both these papers studying sick leave in Sweden are very similar in their focus on contemporaneous social effects.[9] This paper, in contrast, focuses on the long run adaptation in the demand for social insurance benefits.

[8] See the handbook edited by Benhabib, Bisin, and Jackson (2010).

[9] Similar evidence on sick leave is found in Italy, see Ichino and Maggi (2000).

Furthermore, the effects of social norms have been studied in the context of unemployment insurance, a related social insurance program, see Eugster, Lalive, and Zweimueller (2012), Stutzer and Lalive (2004), and Clark (2003). None of these studies of social interactions have analyzed the intertemporal adaptation process, which I do.

3 The Sick Leave Program

Sweden has a generous publicly run sick leave insurance program that covers lost earnings in the case of basically any injury or illness.[10] It is very easy to claim the benefits. For the first week of each spell, the law gives the individual the discretion to determine if he is fit to work or not. If he wants to claim the sick leave benefits he makes two phone calls, one to the social insurance office and one to his employer.[11] There is no fixed allocation of sick leave days, you can use the insurance as long as your sickness requires and for as many spells as you like. For spells up to 7 days the individual himself determines if he is fit to work. For spells longer than 7 days it is required that a physician validates your condition.[12] Monitoring of actual sickness is very light, at least in part due to the difficulty in verifying conditions like stomach ache and back pain.

The program is similar to any social insurance. It pays out benefits if the individual is hit by some shock. In the sick leave program it is a health shock, while unemployment benefits cover unemployment shocks and pensions pay out based on age. What sets the sick leave program apart is the level of individual discretion with respect to claiming benefits. The decision to claim benefits rests entirely with the individual, and observed take up behavior is purely driven by the demand for benefits. This is the case for short spells, which do not require a doctor visit. By focusing on take up, rather than days of leave, I can measure

[10] In a comparison to the U.S. the program encompasses both 'personal days' provided in employment contracts (although restricted to sick leave) and the workers' compensation program.

[11] Benefits are paid by the social insurance office directly to the claimant.

[12] Since I analyze the extensive margin, the validation by the physician is not relevant in this study.

a demand effect unaffected by supply factors like doctors.

The rules governing sick leave insurance have been remarkably constant over the 1974-1990 period. The sick leave program was first passed into law in 1962 (SFS 1962:381) and it took effect in 1963. Data on sick leave are available from 1974, when sick leave benefits became taxable income.[13] The replacement rate for lost earnings due to sickness was set to 90 percent. The daily benefit is calculated as 90 percent of normal annual labor earnings divided by 365, up to a cap. The replacement cap is indexed to the so called base amount, which is related to inflation. About 93 percent of the incomes are below the cap, and 6 percent of the sick leave observations are above the cap.

Benefits can be claimed from the second day of the sickness spell. The definition of the second day is, however, quite generous. It is sufficient to call in sick before midnight and that day counts as the first day of the spell. If you think you'll be sick tomorrow you can always call in sick today and the first unpaid day is of no consequence, and if it turns out that you're fit for work tomorrow you can change your mind. This system was in place until 1987. From 1988 through 1990 the first day of no coverage was abolished.[14]

Most sick leave spells are short, about 95 percent are shorter than one month (Source: Försäkringskassan). You need to have earnings for six months in order to qualify for the sick leave benefits and be less than 65 years of age. The program is universal and it is administered by the central government and does not depend on your employer. Benefits are financed through a flat pay roll tax.

4 Data

I use registry data on individual panels over the period 1974 to 1990 (from 1973 for lagged income).[15] I follow a random sample of the 1974 population for 17 years. The baseline regression has just short of 2 million observations based on

[13] The updates to the program are detailed in law SFS 1973:465.

[14] The updates to the program are detailed in law SFS 1987:223.

[15] The analysis ends in 1990 since later reforms make the data hard to compare. The employers take over sick leave payments for the first two weeks of each spell, which is not observed in the data. Such longer term sick leave is very different from what is analyzed here.

the behavior of about 160,000 individuals. Birth cohorts from 1917 to 1963 are included. About 3 percent of the population is sampled.[16] Household members are included in the data, so I can control for the household composition and spousal income. The data draw information from several sources; demographic information from the population registry, income information from the tax authorities, and various public benefits from the social insurance administration. The main dependent variable, participation in the sick leave programs, is defined based on observing positive sick leave benefits during the year. Data on sector of work is available from 1979 and on.

Table 1. Summary statistics.

	Mean	Std. Dev.	Min	Max	Obs.
Sick leave participation	0.637	0.481	0	1	1930462
Year of birth	41.9	11.3	17	63	1930462
Earned income, lagged	127519	319262	0	1.99E+08	1929137
Capital income, lagged	1748	57136	0	4.81E+07	1929137
Age	40.0	10.7	22	60	1930462
Man	0.525	0.499	0	1	1930462
College, 3+ years	0.113	0.316	0	1	1930462
< 3 years college	0.091	0.287	0	1	1930462
High school	0.380	0.485	0	1	1930462
Married	0.602	0.490	0	1	1930462
Months with infant x Woman	0.101	0.757	0	7	1930462
Children aged 7 months to 2 years	0.064	0.249	0	4	1930462
Children aged 3 to 6 years	0.131	0.341	0	3	1930462
Children aged 7 to 15 years	0.286	0.460	0	3	1930462
Husband's income, lagged	56178	288605	0	1.68E+08	1929137
Wife's income, lagged	26976	57974	0	2.10E+07	1929137
Employment rate, by county	0.870	0.021	0.807	0.912	1930462
Average earnings, by county	130946	14071	94790	173337	1930462

Sample: Labor force participants, 22-60 years old. Amounts in 1990 SEK.

Individuals are included in the analysis from ages 22 to 60. The age restrictions are due to the looser connection to the labor market of individuals at the tails of the life cycle. The young may still be studying and may not have a firm foot in the labor market. At ages close to retirement individuals face a number of incentives to leave the labor force that aren't modeled here, and those observations are excluded. Since the sick leave program is designed to replace lost labor earnings, the analysis is restricted to individuals who are labor force

[16] The only sampled individuals who disappear from the data are those who die or emigrate. For further details on sample selection and data coverage see Edin and Fredriksson (2000).

participants.[17] Summary statistics are presented in Table 1.

5 Increased Demand For Social Insurance

5.1 Aggregate Trends

It is possible the raw averages in Figure 2 capture life cycle patterns, for example, young generations are observed when they have young children that may make them take more sick leave during those years.[18] Figure 3 plots the average take up by age for four different cohorts where cohorts can be compared at the same stage in the life cycle. Men are plotted in the left panel and women on the right. Across the entire life cycle, younger generations have higher take up. The pattern is particularly pronounced for women.[19]

There may be concerns that changes in labor force participation are behind the increasing sick leave take up across generations.[20] For women the labor force participation rates have increased across generations and the 1955 cohort of women have rates similar to men. Men's labor force participation rates have been constant across generations (along the life cycle paths), indicating that labor force participation changes don't explain the increased sick leave take up. This issue is examined further below.

Comparing the cohorts that are of age 25 and 45 in 1974, born in 1929 and 1949, I find that the share that never takes sick leave has dropped from 13.8 to 1.6 percent. Further evidence on this shift in the distribution of sick leave across cohorts is presented in Figure 4. The figure plots the distribution of how often individuals use the sick leave program across cohorts.[21] For the oldest cohort

[17] Labor force participation is defined as having positive labor earnings during the year.

[18] There are at least two causes for this. Parents may use the sick leave program to take care of sick children, or sick children make the parents sick.

[19] Note also that there is no drop off after the main child rearing ages, indicating that this factor does not drive the cohort trend.

[20] This would be a concern if the marginal labor force participants are more prone to use sick leave.

[21] For each individual I've computed the number of years of sick leave participation when in the labor force, divided by the number of years in the labor force. The fraction has been scaled by multiplying by 17, so the histogram expresses what number of years out of 17 that individuals used the program.

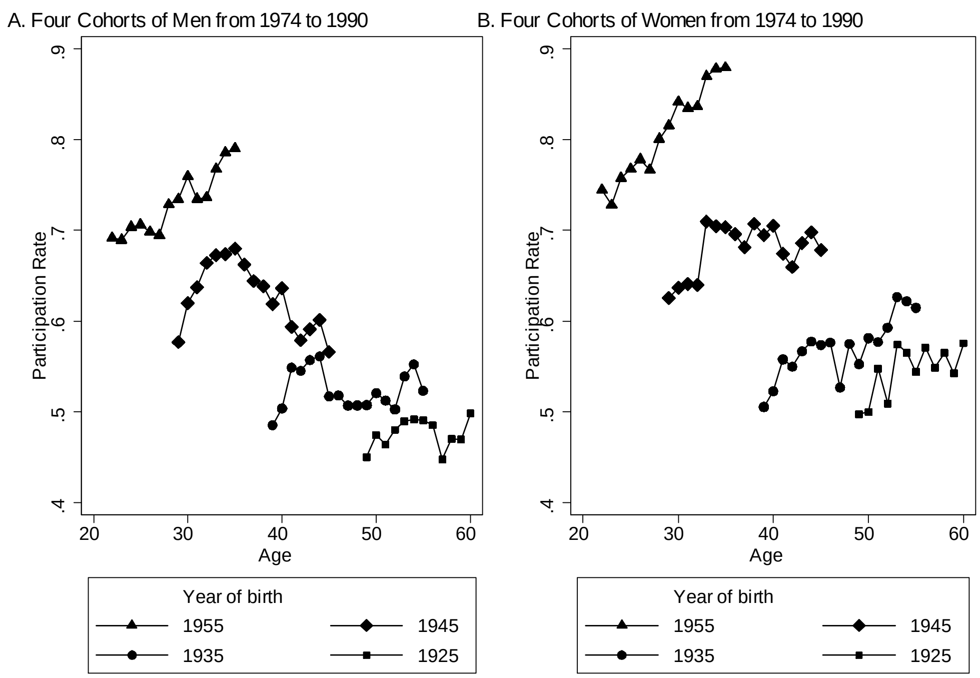

Figure 3: Sick Leave Participation for Men and Women. Sample: Labor force participants, ages 22-60.

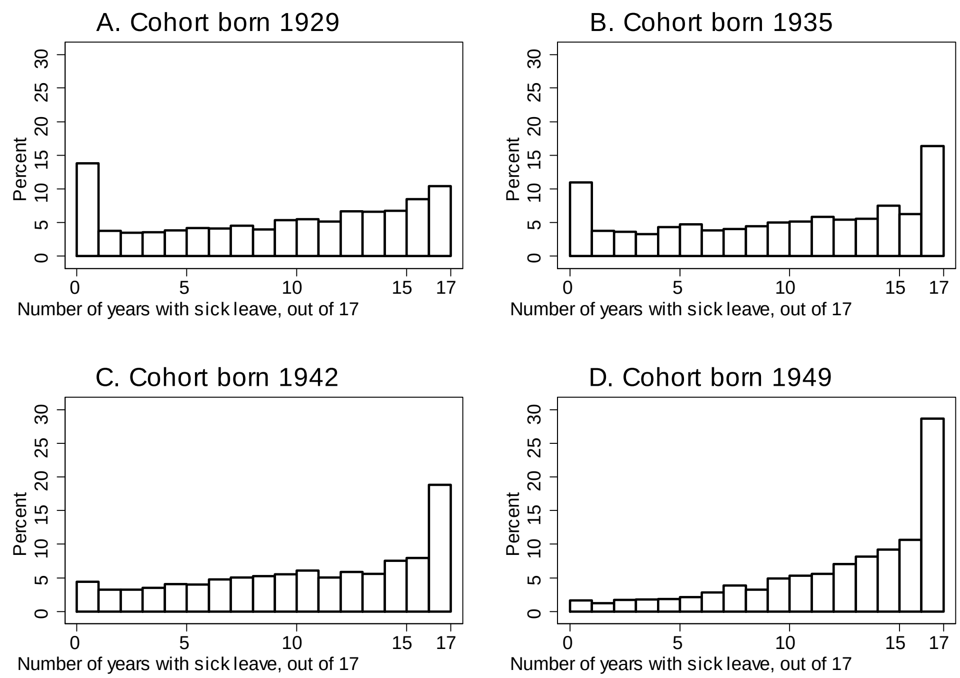

Figure 4: Distribution of Sick Leave Across Cohorts.

born in 1929 the mode of the distribution is to never use the program. For the next cohort born in 1935 the mode has shifted to always using the program. The shift from infrequent to frequent use of the program continues for the cohort born in 1942, and it is most pronounced for the cohort born in 1949.

5.2 Baseline Regression

So far only raw averages have been presented. Column 1 of Table 2 presents the average slope of the cohort trend, 0.8 percentage point per year, which adds up to a 16 points higher take up rate for a cohort born 20 years later than the base cohort. The results are from using the pooled ordinary least squares (OLS) estimator. This estimator only uses the variation across individuals as the year of birth does not vary over the life cycle.

One concern may be that the raw average is confounded by life cycle patterns, which may vary by groups as seen in Figure 3. I include a full set of interactions between gender, the four education groups,[22] age and age squared. Including these controls raise the estimated cohort trend as seen in column 2, indicating that life cycle patterns mask an even stronger cohort trend.[23] If parents with young children take more sick leave, and these parents are mostly observed among the younger cohorts, it may bias the estimate of the cohort trend upwards. Detailed controls of the number of children at different ages are included in column 3, and the estimated cohort trend is similar to the previous specification.

Younger cohorts tend to have higher education and may have higher earnings (conditional on age) than older cohorts. If sick leave is a normal good, it could be that the higher take up rate is in part an income effect. I control for own earnings and capital income as well as the spouse's income (if present). The income variables are lagged one year since current income and sick leave take up may be jointly determined. I also control for regional business cycles (through

[22] The four education groups are 3 or more years of college, less than 3 years of college, high school degree, and less than a high school degree.

[23] The average age pattern of sick leave is increasing over the relevant working age range, albeit at a decreasing rate.

the regional employment rate) and regional fixed effects.[24] These controls do not affect the cohort trend much, as seen in column 4.

Table 2. Cohort trend in sick leave program participation.

Dependent Variable: Indicator of Positive Sick Leave
Pooled OLS Estimator

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Year of birth	**0.008**	**0.011**	**0.011**	**0.010**	**0.011**	**0.010**
	(.0003)	(.0005)	(.0003)	(.0004)	(.0004)	(.0004)
Age, age sq interacted with gender and education		Yes	Yes	Yes	Yes	Yes
Months with Infant x Female			Yes	Yes	Yes	Yes
Child 7 months-2 years			Yes	Yes	Yes	Yes
Child 3-6, Child 7-15 years			Yes	Yes	Yes	Yes
Marital status			Yes	Yes	Yes	Yes
Income lag				Yes	Yes	
Capital income lag				Yes	Yes	Yes
Spouse's income lag				Yes	Yes	Yes
Business cycle control				Yes	Yes	Yes
Regional fixed effects				Yes	Yes	Yes
Permanent income					Yes	
Permanent income spline						Yes
Income lag spline						Yes
Observations	1955691	1930462	1930462	1929137	1929137	1929137

Notes: Education is gouped into 3+ years of college, <3 years of college, high school, <high school.
Months with infant counts the number of months there is a child of up to 7 months of age.
Business cycle control is average regional employment rates.
Permanent income is an estimated individual fixed effect of earnings on demographic interactions and BC controls. Spline is 5 piece with knots at quintiles.
Individual panel data from 1974-1990, annually. Estimates of the pooled OLS estimator.
Standard errors, clustered by birth cohort, in parenthesis.
Sample: Labor force participants, 22-60 years old.

It is possible that not only current earnings but lifetime earnings affect the sick leave choice. Using the panel data, I run an individual fixed effect (within) regression of individual earnings on the age-gender-education interactions mentioned above and business cycle controls. The individual fixed effect from that

[24] The objective is not to explain regional differences in take up. There are 8 regions.

regression is the measure of permanent income, which I include in the regression in column 5. Permanent income has little impact on the cohort trend.

Linearity of the income effects may be a strong assumption that is relaxed in column 6. I construct five piece splines of both permanent income and lagged income.[25] This allows the income effects to differ across quintiles both for permanent and lagged income. The estimated cohort trend remains stable at 1 percentage point per birth cohort. The specification in column 6 is the baseline in the analysis below.

5.2.1 Non-Linearity

I replace the linear cohort trend assumed in Table 2 with fixed effects for each cohort. The estimated coefficients, after having accounted for all the controls in specification 6, are plotted in Figure 5.[26] The cohort effects are quite close to a linear trend, so the linearity assumption does not seem to drive the result.

5.2.2 Health Trends

Deteriorating health for younger cohorts could be an explanation for the cohort trend. Measures of health outcomes, however, paint a different picture. Younger cohorts have improved health along objective measures. Expected remaining longevity at age 20 increased by 1.76 years for men and 2.16 years for women between the early 1970's and the late 1980's. The occurrence of heart problems has decreases as well. For the 45-64 age group the average rate of heart problems during 1980-1982 was 5.0 percent. These problems had decreased to 3.2 percent in the 1990-1992 period (Source: Statistics Sweden). The fraction of the population 16-84 that report that their health status is generally good has increased slightly from 74 to 75 percent between 1980 and 1990. Cancer mortality has decreased across cohorts. Among 30-34 year old women in the late 1960's the mortality of cancer was 21 per 100 000 persons. In the early 1990's the rate had dropped to 13.5. The corresponding rates for men

[25] The results are robust to using 10-piece splines.
[26] Being born in 1917 is the omitted category.

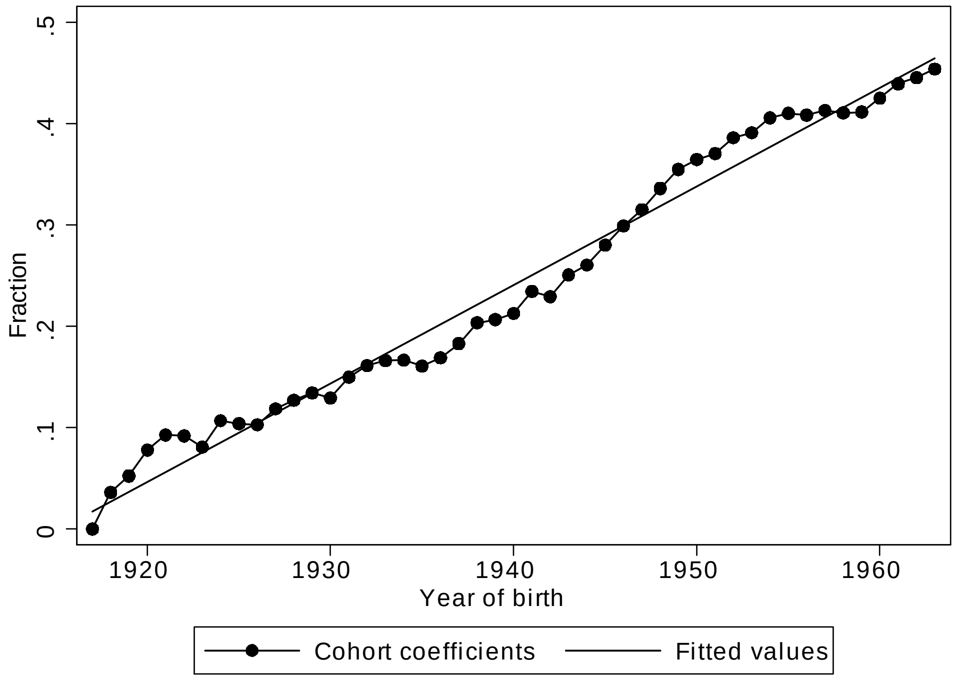

Figure 5: Cohort Fixed Effects for Sick Leave Participation. Note: Estimated cohort effects after controlling for demographics, income, etc.

were 16.7 and 11.2. Reductions in mortality rates are seen at most points in the age distribution across cohorts (Source: NORDCAN). Improvements in health conditions across cohorts make the sick leave trends more surprising.

5.3 Robustness

Even though a host of factors were controlled for above there may still be alternative explanations to the trend. One concern may be the measurement of sick leave benefits. Up until 1983 maternity leave was included in sick leave benefits but starting in 1984 the parental leave in connection to the birth of a child was reported separately. In addition, care for sick child was reported separately from 1987. The sick leave variable is redefined as take up of any of the three programs (sick leave, parental leave, and care for sick child), but it does not affect the estimated cohort trend as seen in specification 1 in Table 3.[27]

Since sick leave is not the only program individuals may use it is possible that there is some shifting across programs, which could influence the estimate. To examine the sensitivity to the use of other programs I exclude individuals who have taken up either unemployment benefits or welfare payments during the year. The estimated cohort trend in specification 2 in Table 3 is slightly lower with this sample restriction, indicating a stronger trend among individuals that use other programs.[28, 29]

As the main regressions condition on being in the labor force there may be concerns that individuals that have left the labor force would have been on sick leave if they had remained in the labor force. In particular, there may be concerns that among the older people only the healthy remain in the labor force, which could drive the finding. To address this concern the sample is restricted to those between 22 and 45 years of age, where there is little exit from the labor force. This restriction does not affect the cohort trend as seen in specification 3 in Table 3.[30]Another approach is to assume that everyone outside the labor force would have been on sick leave had they been in the labor force. I redefine sick leave such that all individuals outside the labor force are added to the sick leave rolls (and there is no longer a sample requirement on being in the labor force). The estimated trend is similar also in this specification. Changes in

[27] It's possible that young children are not appropriately controlled for by the linear controls. To address this I exclude women with children between the ages 0 and 2 (only women since care of young children were mostly done by women during the period we study). Excluding this group does not affect the cohort trend.

[28] Employers do not seem to collude with young workers. During slow times there may be an incentive for the employer to reduce cost by inducing employees to take sick leave (paid by the government). Younger workers with less job protection may be more likely to enter into such an arrangement, which potentially could explain the cohort trend. I include sector fixed effects interacted with an indicator if the person is less than 30 years old. It does not have a large impact on the cohort trend.

[29] The cohort trend is also robust to controlling for tax rates. Ljunge (2012b) finds that tax rates affect sick leave, but tax rates don't vary systematically across cohorts in a way that can explain the take up trend across cohorts.

[30] Another compositional story relates to immigrants. I include an indicator of being born outside Sweden as well as the fraction of the working age population in your community that is born outside Sweden. Including these controls increase the cohort trend somewhat.

labor force composition can't explain the cohort trend.

The fifth specification examines if the cohort trend could be explained by different take up rates across time by including year fixed effects. In this specification the age controls have to be excluded in order to identify the cohort trend (but the gender-education interactions are included). The estimated cohort trend is still large and significant indicating that the cohort trend can't be explained by generally rising demand for benefits.

Table 3. Alternative explanations of cohort trend in participation.

Dependent Variable: Indicator of Positive Sick Leave

Alternative explanation:	Program definition	Use of other programs	Labor force composition 1	Labor force composition 2	Secular drift
Specification	(1)	(2)	(3)	(4)	(5)
Year of Birth	**0.0099**	**0.0094**	**0.0105**	**0.0102**	**0.0062**
	(.0004)	(.0004)	(.0003)	(.0004)	(.0002)
Additional controls or sample restrictions	Broader sick leave measure	Exclude people with UI benefits, welfare.	Include only ages 22-45	Redefine all outside labor force as on sick leave	Year fixed effects, age terms excluded
Observations	1929137	1820117	1292152	2183324	1929137

Notes: All controls used in Table 2, column (6), are included if applicable.
Individual panel data from 1974-1990, annually. Estimates of the pooled OLS estimator.
Standard errors, clustered by birth cohort, in parenthesis. Sample: Labor force participants, 22-60 years old.

The model has been estimated for men and women separately. The cohort trend is a bit stronger for women, and in particular unmarried women.[31] Estimating cohort fixed effects by gender also show a close to linear cohort trend, and women on average have higher take up rates than men across birth cohorts.[32]

[31] Part of this difference could be due to women working more in the public sector, where take up rates are higher.

[32] The average take up rates by cohort, for women and men separately, are plotted in Ljunge (2011).

5.3.1 Unemployment Insurance

Running the baseline regression with unemployment insurance take up, rather than sick leave, as the dependent variable produces a significant cohort trend towards higher take up rates for younger cohorts.[33] The finding supports the hypothesis that the cohort trend is prevalent more generally. Unemployment insurance is a social insurance program just like the sick leave program. Unemployment insurance is, however, different in several respects. There are some supply side restrictions like verification that the beneficiary is not employed and that the beneficiary is required to register with the unemployment office.[34]

6 A Mechanism: Reference Group Influence

The decision to claim social insurance benefits may be influenced by a non-monetary cost (Moffitt, 1981). The more common it is to claim social insurance benefits among your reference group, the lower may be the non-monetary cost. In particular, following Lindbeck, Nyberg, and Weibull (2003), reference group influence may not adjust instantaneously to behavior in the reference group but with a lag. If the non-monetary cost changes slowly, behavior may adapt for a long time before reaching a steady state.

6.1 Model

Consider a simple model of individual choice similar to Lindbeck, Nyberg, and Weibull (2003), where individuals can choose to claim benefits or not. If benefits aren't claimed individuals consume their labor earnings.[35] If benefits are claimed the worker consumes a fraction ρ of his earnings (ρ represents the replacement rate), enjoys some extra leisure, and suffers non-monetary cost γ.

[33] The finding of a significant cohort trend is robust to a specification with year fixed effects.

[34] Lemieux and MacLeod (2000) examines the long run increase in unemployment insurance take up in Canada.

[35] Earnings may be after tax, where the tax revenues not used for the social insurance program are used for government consumption that may be valued by individuals but it is separable from private consumption and independent of social insurance take up.

The preferences of individuals are represented by

$$u = \begin{cases} \ln w - \beta & \text{if no take up} \\ \ln \rho w - \gamma & \text{if take up} \end{cases} \tag{1}$$

where $w > 0$, $0 < \rho \leq 1$, and $\gamma \geq 0$. β is the valuation of leisure (it may be negative or positive) that varies between individuals.[36] The valuation of leisure is distributed according to cumulative distribution function Φ, with positive density on the whole real line. I may also allow for heterogeneity in w across individuals and time.

There is a valuation of leisure that makes an individual indifferent between taking up benefits or not. Denote this valuation of leisure by $\beta^* = -\ln \rho + \gamma$. The take up rate of the social insurance benefit in the economy, call it z, corresponds to the fraction with $\beta > \beta^*$, that is,

$$z = 1 - \Phi\left(\beta^*\right) \tag{2}$$

The current non-monetary cost depends on the share of transfer recipients in group m in the previous time period; $\gamma_t = h\left(z_{m,t-1}\right)$.[37] Furthermore, $h : [0, 1] \rightarrow \mathbb{R}_+$ and h is continuously differentiable with $h' \leq 0$.

Individuals take prices, preference parameters, and $z_{m,t-1}$, and hence the non-monetary cost, as given. The equilibrium outcome in period t is a take up rate for each group n, $z_{n,t}$, who is influenced by past behavior of group m, such that

$$z_{n,t} = 1 - \Phi\left[-\ln \rho + h\left(z_{m,t-1}\right)\right]. \tag{3}$$

In a steady state (3) holds for any n, m, t.

I assume that the parametric specification for the non-monetary cost is

$$h\left(z_{m,t-1}\right) = s_0 - s z_{m,t-1} \tag{4}$$

where $s_0 > s > 0$. This model is taken to the data on sick leave take up in Sweden. An individual will take up the benefits if $\ln \rho + \beta - s_0 + s z_{m,t-1} > 0$.

[36] In the estimation below there aren't any parameter restrictions imposed.

[37] The non-monetary cost may be internal or external stigma, which depend on the reference group's behavior. Another interpretation is that γ is an information cost and reference group behavior lead to social learning about the program that affects the cost.

Factors that may be allowed to influence the sick leave choice are captured by a vector $x_{i,t}$ for individual i in period t with an associated parameter vector δ. These factors may be interpreted as capturing differences in the valuation of leisure.

This results in an empirical model of sick leave for individual i, a member of group n, in period t, $SL_{i,n,t}$, which takes on the value 1 if any sick leave benefits are claimed during the period and 0 otherwise. Define the latent variable $SL^*_{i,n,t}$ such that

$$SL^*_{i,n,t} = \alpha + x_{i,t}\delta + sz_{m,t-1} - \epsilon_{i,t} \tag{5}$$

$$SL_{i,n,t} = \begin{cases} 1 & \text{if } \; SL^*_{i,n,t} \geq 0 \\ 0 & \text{if } SL^*_{i,n,t} < 0 \end{cases} \tag{6}$$

α captures all constant parts of the model. It is possible to recover the slope coefficient in (4) from the data. Unobserved influences, assumed to be i.i.d., are captured by $\epsilon_{i,t}$. The generosity of the program, captured by the replacement rate ρ, does not affect the influence of reference group behavior. The replacement rate is part of the constant which only affects average take up.

In this model the expectation might have been to see an S-shaped curve in Figure 2 as would happen in a standard adoption model, see for example Fernandez (2011).[38] These models do, however produce a long straight segment just like in Figure 2. For even younger cohorts one would expect a tapering off of the curve as take up get closer to 1. There is at least a hint of this as the cohorts from the early 1950's are above the regression line in Figure 5 while the cohorts from the late 1950's and 1960's are below the line. For the oldest cohorts there is no exponential take-off from very low levels. It may be that the increasing demand trend started before 1974 during the less generous program and that it would be observed it if data from the earlier period was available. It could also be that the underlying distribution of preferences is not symmetric, which could produce a more linear shape also for the oldest cohorts.

[38] The S-shaped curve is similar to the cumulative density function of a Normal distribution.

6.2 Reference groups

Role models set a standard for acceptable behavior. Such mechanisms have been discussed in the developmental psychology literature, see for example Harris (1995, 1998).[39] Anthropologists who have studied sick leave in Sweden point to the influence of the behavior of other individuals in the community as determinants of individual sick leave behavior, see Frykman and Hansen (2005, 2009) as well as Frykman et al (2009). These anthropologists stress how individuals respond to changes in social influences and that communities adapt to welfare state institutions at different speed.

The reference groups are intended to capture 'synthetic colleagues,' as the most direct influence may be from colleagues who share the same professional characteristics, who live and work in the same area.[40] Individuals who are a few years older and a bit ahead in their careers may serve as role models for the individual's current decision. To capture the idea that colleagues influence individual's sick leave decisions I define the reference groups based on age, education, sector, geographic area, and birth cohort. In the reference group definitions I distinguish between two education groups, some college or none, and two sectors, private or public. This definition of the reference group as colleagues can't make use of the first few years of the sample period since the information on sector is not available.

In line with the model I allow for the reference group influence to be affected by the fraction of the reference group that takes up the social insurance benefits.[41] I assume that individuals may be influenced by the behavior of older cohorts in a past year. When studying individual sick leave behavior I relate it to the reference group m's average sick leave take up denoted by z_m. Reference group m is the cohort born 2-4 years earlier than the individual in question

[39] There is also quantitative evidence that individuals are affected by people in their environment, see for example Bertrand et al (2000) and others discussed above.

[40] Matched worker-employer data are not available for this period when the sick leave program rules are constant and take up captures demand for the benefits.

[41] There is no a priori restriction of a positive relationship between the subject and the role model. I allow for a negative relationship between the role models and the individual. Role models would then provide 'cautionary tales.'

in the same education and sector group living in the same county.[42] The time lag is 3 years.[43] The adjustment of reference group influence is hence slow in two dimensions, through the influence of older cohorts on younger cohorts, and through the time lag. The cross cohort lag is motivated by the influence of role models, that individuals are influenced by those a few years ahead on the career ladder. The time lag captures that the non-monetary cost may not adjust instantaneously but with a lag; it could for example take a few years for individuals to observe the impact of sick leave on their role models' careers.

The results don't rely on the exact definition of the reference group or the time lag. I allow for reference groups that do not differentiate by education and sector, which corresponds closer to reference groups as neighbors. The results are also similar with alternative specifications of which cohorts are in the reference group and for alternative time lags as discussed below. I don't interpret the specification to be the one and only social influence on individual behavior. Rather, the specification captures, in an empirically tractable way, an intergenerational spillover that is essential in the model to explain the behavior across generations in Figure 2.[44] The average size of the reference group corresponding to colleagues is 56 and for neighbors the average size is 269 individuals.

7 Results

The model postulates a direct relationship between reference group behavior and individual behavior. This relationship can be estimated in the data. Under the assumption that the model is an accurate depiction of the real world (conditional

[42] I choose the county level for two reasons. The county is an area within which most people live, work, and socialize. For practical reasons, there is also the need for a sufficient number of individuals of each age to compute reference group behavior. Lower levels than the county may be problematic for this reason.

[43] For example, the reference group behavior in the year 1985 for an individual born 1955 is the average of the sick leave take up in 1982 of those born between 1951 and 1953 who live in the same county and belong to the same education-sector group. There are 24 counties in Sweden.

[44] For example, I don't necessarily believe that all social effects relate to only those born 2-4 years earlier. However, looking at those 2-4 years older is sufficient to capture an important mechanism that has not been studied before.

on the control variables) the slope parameter in the reference group influence function (4) is estimated, which has a structural interpretation. This would provide a clear insight for policy design by quantifying the multiplier effect of an increased take up rate of the social insurance benefits for some age group. All else equal, program expenditures may increase for a long time due to the effect on reference group influence, which induce other individuals to take up the benefits, and so on.[45] It also implies that the long-run behavioral response to a change in program generosity may be much larger than the short-run response.

If the real world is more complex than the model then the interpretation of the estimates may change. It is possible that the true reference group influence is unobserved, that is, the non-monetary cost is an omitted variable like attitudes and beliefs of the reference group that in turn affect individual behavior.[46] Reference group behavior may then capture these attitudes and beliefs, but the estimated slope parameter in (4) would not have a structural interpretation if the non-monetary cost function is not correctly specified. An increase in benefit take up of the reference group would not necessarily have a multiplier effect on other's take up. The multiplier effect would in this case only materialize if the increased benefit take up in the reference group is caused by a change in underlying attitudes and beliefs in the reference group.

7.1 Colleagues

Table 4 presents estimates using both the pooled OLS and the within estimators.[47] The estimates from the two methods have distinct interpretations, which are explored. The first three specifications use the pooled OLS estimator.[48] The estimate on the reference group behavior is to a large extent identified from variation across individuals. The reference groups are based on the mea-

[45] The intergenerational mechanism has the potential of explaining the pattern in Figure 2, in contrast to a purely spatial mechanism since generations are not systematically separated spatially.

[46] In this case we would not be able to distinguish exogenous social interactions from correlated effects as discussed by Manski (1993).

[47] Included are the same individual and aggregate controls as in specification 6 in Table 2, except for year of birth.

[48] The estimator assumes that individual effects are randomly distributed.

sure of colleagues, which exhibit variation across 41 birth cohorts, 4 skill-sector groups, and 24 counties. The coefficient on reference group behavior is positive if individuals whose reference group have relatively high sick leave take up (3 years earlier) themselves have relatively high sick leave take up. The estimate is 0.47 as seen in the first specification in Table 4. Under the strict assumptions of the model (no omitted variables that affect the estimate) the slope estimate captures the influence of the reference group (s in the model).

However, if unobservables are allowed, for example initial individual conditions like work norms instilled by parents, which are correlated with average reference group behavior, then the estimate picks up both effects. Then the estimate is a combination of reference group influence and individual fixed characteristics. To examine if the pooled OLS estimate of the reference group influence is picking up some unobserved characteristic of individuals that differs across generations I proceed in two steps. First, I account for a time invariant reference group influence in the pooled model. Second, I estimate the model accounting for unobserved fixed characteristics using the within estimator. In specification 4 in Table 4 I include the reference group sick leave behavior in the first period observed, which is a constant value for each reference group.[49] This value is a parameterization of the initial influence of the reference group that stays constant across the life cycle. The value of the reference group behavior in year t-3 varies across time within each reference group and capture the time varying influences. The estimate on the time varying influence is approximately reduced by a third in specification 4 compared to specification 1, and the time invariant influence comes in positive and strongly significant. The relative magnitudes of the estimates in column 4 indicates the relative importance of time varying versus time invariant influences.

Including individual fixed effects is a non-parametric way of accounting for all fixed influences on sick leave behavior, compared to the parametric approach just discussed. In the within case the estimate is identified from variation in

[49] This is the value observed in year 1979 for most reference groups, and a later year for a few cohorts that enter the sample after 1982.

reference group behavior within the same individual.[50] The individual fixed effect would capture any influence of work norms instilled by parents and any time invariant influence from the reference group.[51] A significant estimate of reference group behavior would support the presence of time varying influences, that there is an influence of the non-monetary cost on individual behavior within the life-cycle while accounting for unobserved individual characteristics. The estimate of 0.12 is obtained with the within estimator as seen in specification 5 in Table 4, and the estimate is strongly significant.[52]

[50] The estimate is positive if the individual is more likely to take up sick leave in periods when the reference group of older people's lagged take up is relatively high.

[51] The fixed effect also captures for example labor market turbulence, which may affect cohorts differentially. Younger generations, who tend to have less job tenure and employment protection may be more subject to this turbulence. Ichino and Riphahn (2005) find that workers increase their sick leave substantially when employment protection kicks in. I find that young generations use sick leave more than the older in spite of these effects.

[52] Standard errors are adjusted for clustering on birth cohort. This level of clustering allows for arbitrary correlations of error terms across years, skill groups, and counties within each birth cohort.

Table 4. Reference group behavior (colleagues) and sick leave participation.

Dependent Variable: Indicator of positive sick leave benefits
Linear probability model regressions

Reference group	Colleagues: Cohorts born 2-4 years earlier in individual's sector and skill group, living in individual's county					
Time lag	3 years					
Estimator	Pooled	Pooled	Pooled	Pooled	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)	(6)
Reference group sick leave behavior in year t-3	**0.468**	**0.457**	**0.458**	**0.333**	**0.123**	**0.124**
	(.016)	(.016)	(.016)	(.016)	(.01)	(.01)
Reference group sick leave behavior in first year observed				**0.215**		
				(.015)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year trend		Yes				
Year fixed effects			Yes	Yes		Yes
Observations	932917	932917	932917	932917	928312	928312

Notes: Controls include age and age sq interacted with gender and education, household composition, marital status, capital income and spousal income, average county earnings, and regional fixed effects.
5 piece splines of lagged income and permanent income included. Splines have knots at quintiles.
Individual panel data from 1979-1990, annually. Estimates of the pooled and within estimators.
Standard errors, adjusted for clustering on birth cohort, in parenthesis.
Sample: Labor force participants, 22-60 years old. There are 24 counties.

There is a significant impact of reference group behavior on sick leave take up in the estimation across individuals also after accounting for flexible time effects. In specification 2 in Table 4 a linear time trend is included in the pooled OLS estimation, which controls for a linear increase in the demand for sick leave over time. The coefficient estimate on reference group behavior remains similar in magnitude and significance. I also allow for non-linearities in the time effects by including time fixed effects, which account for any aggregate influences on sick leave, in specification 3 in Table 4.[53] Again, the coefficient estimate on the

[53] The time effects are in part identified from the fact that not all individuals are in the analysis all years, for example, the youngest cohorts are not observed in the 1970's. The time effects hence mechanically absorb some of the variation across cohorts.

reference group behavior remains similar to the previous specifications. An alternative approach to account for changes over time and generations is to include cohort fixed effects rather than the time effects. Such a specification also produces a positive and highly significant estimate on the influence of the reference group's behavior.

The influence of older generations account for between two-fifths and half of the increasing demand across generations, depending on the specification. The average reference group take up for the cohort born in 1930 is 52.0 percent. For the cohort born in 1950 the corresponding take up is 68.9 percent. By multiplying the difference with the pooled estimate of 0.46 in column 1 of Table 4 the reference group's influence increases the younger cohort's take up rate by 7.8 percentage points, which is about 40 to 50 percent of what was estimated in Table 2.[54]

Including year fixed effects in the within estimator alters the interpretation on the estimated coefficient of reference group behavior.[55] Without year fixed effects the coefficient is identified from mean deviations of reference group behavior. With year fixed effects the within coefficient estimate is identified from mean deviations of reference group behavior *and* mean deviations from the national average take up, basically a double difference. The estimated coefficient in specification 6 of Table 4 indicates that the influence of reference group behavior conditional on national behavior is similar to not conditioning on national behavior.[56]

7.1.1 Instrumenting for reference group behavior

To further examine the hypothesis an instrument is used to produce exogenous shifts in sick leave behavior of the reference group. I use mortality rates cor-

[54] The raw average in column (1) of Table 2 indicates a 16 percentage point higher take up rate for the cohort born 20 years later. The estimate in column (6) of Table 2 produces a 19.6 percentage point higher take up rate for the younger cohort.

[55] Introducing a linear time trend is not meaningful in the within context since age is already controlled for, which contains the same variation as a time trend.

[56] The estimate in specification (6) is not directly comparable to specification (3) since the pooled estimate does not have a similar double difference interpretation.

responding to the cohorts and locations of the reference groups to instrument for reference group behavior.[57] The idea is that mortality rates are the result of serious health shocks, which also affect sick leave take up. Implicitly, I only consider variation in reference group behavior that is correlated with these serious health shocks.[58] Mortality rates are decreasing across cohorts while sick leave is increasing across cohorts. The aggregate trends are hence stacked against finding a positive influence of mortality on sick leave, as I hypothesize.

I observe mortality rates per 1000 population by year, age and county. Mortality rates are assumed to follow a simple model with a second order polynomial in age and a random shock. Denote the mortality rate in county c, for the generation born in year g, in year t by $MR_{c,g,t}$ then

$$MR_{c,g,t} = \alpha_0 + \alpha_1 Age_t + \alpha_2 Age_t^2 + \varepsilon_{c,g,t} \tag{7}$$

Mortality shocks are assumed to be i.i.d. across counties, generations, and years. The model explains about 85 percent of the variation in the data. As the main regression includes controls for age and its square it's only the remaining variation in the error term that is used to provide exogenous variation in reference group behavior. I could also allow more complex models of mortality, for example with year fixed effects[59] but it would not affect the analysis in the specifications that control for year fixed effects.

The mortality rates used as instruments are defined as far as possible in the same way the reference group behavior is defined. Since mortality data is not available by education-sector groups, corresponding to the reference group 'colleagues,' the instrument is computed at a higher level. That is, the mortality rate per 1000 of those born 2-4 years earlier by county, lagged 3 years, is used to instrument for the sick leave take up by those born 2-4 years earlier by county

[57] The instrument is not intended to explain the cohort trend in sick leave, the mortality rate just provides exogenous variation in the reference group's behavior.

[58] These serious health shocks contrast with arguably less serious shocks to the value of leisure such as big athletic events, see Skogman-Thoursie (2004).

[59] Adding year fixed effects to the model increases the explanatory power by about 1 percentage point. In a model with year effects I could relax the assumption that health shocks are independent across counties and allow for common time trends.

and education-sector group, lagged 3 years.[60] The identifying assumption for this approach is that older cohorts' mortality rates have no direct impact on individual sick leave decisions three years later. The only impact comes through the older cohorts' behavior.[61]

The models are estimated by two stage least squares (2SLS). The instrument exhibits variation across counties, generations, and years. The first stage regressions show a positive relationship between mortality rates and sick leave up take as hypothesized. The instrument is not weak.[62] The first stage results are reported in Table A1 in the appendix.

The second stage results are presented in Table 5. The first estimate from the pooled 2SLS estimate is 0.72. Including a year trend produces an estimate of 0.79, larger than without the instrument. The pooled estimate with fully flexible year effects is 0.76, again a bit larger than the OLS estimate. Instrumenting has a big impact on the within estimates, which are now larger in magnitude compared to the results without instruments. The within estimate is 0.79 in column four.[63] With year fixed effects the estimated coefficient is 0.66, as seen in specification 5 in Table 5.[64]

[60] In the case of the reference group 'neighbors,' which does not distinguish between education-sector groups, the instrument is computed for exactly the same level as the reference group.

[61] More formally, the assumption is that the mortality shocks in (7) for the generations 2-4 years older in year t-3 are uncorrelated with the leisure shocks to the current generation in year t in the main model (5).

[62] The instrument has t-values of at least 5 in first stage regressions, and tests based on Kleibergen-Paap statistics reject the hypotheses of weak instruments and underidentification. The results are robust to including county fixed effects rather than regional fixed effects.

[63] The demographic interactions can be seen as controlling for learning over the life cycle, where the learning follows a second order polynomial for each of the demographic groups.

[64] Pooled and within estimates are very similar, indicating that the estimates are identified from time varying influences. Including the reference group behavior in the first year observed produce similar estimates as reported in the table.

Table 5. Instrumental variable estimates of reference group influence (colleagues).

Dependent Variable: Indicator of positive sick leave benefits
Instrumental Variable/2SLS regressions
Instrument: Mortality per 1000 population for cohorts born 2-4 years earlier by county in year t-3

Reference group	Colleagues: Cohorts born 2-4 years earlier in individual's sector and skill group, living in individual's county				
Time lag	3 years				
Estimator	Pooled	Pooled	Pooled	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Reference group sick leave behavior in year t-3	**0.724**	**0.796**	**0.759**	**0.795**	**0.659**
	(.083)	(.079)	(.075)	(.206)	(.177)
Controls	Yes	Yes	Yes	Yes	Yes
Year trend		Yes			
Year fixed effects			Yes		Yes
Observations	932917	932917	932917	928312	928312

Notes: Controls include age and age sq interacted with gender and education, household composition, marital status, capital income and spousal income, average county earnings, and regional fixed effects. 5 piece splines of lagged income and permanent income included. Splines have knots at quintiles. Mortality rates computed as number of deaths divided by population by age and county cell. Individual panel data from 1974-1990, annually. Estimates of the pooled and within estimators. Standard errors, adjusted for clustering on birth cohort, in parenthesis. Sample: Labor force participants, 22-60 years old. There are 24 counties.

Overall, the estimated influence of role model behavior is larger when instrumenting with mortality rates.[65] Role model behavior shifted by these health shocks has a substantial influence on individual behavior. It indicates that the individuals in the reference groups whose sick leave is shifted by the instrument have a large influence on the behavior of younger cohorts compared to the average behavior of the group. The marginal individuals shifted by the mortality shock could hence have a large effect on the non-monetary cost. It is also possible that instrumenting has removed bias due to mismeasurement of role model influence, which would lead to higher estimates. The estimates in Table 5 are fairly similar across specifications. That the pooled and within estimates

[65] The magnitudes are similar to the effects on high school graduation in Cipollone and Rosolia (2007). Those authors use an earthquake to get exogenous variation in the reference group's behavior.

aren't substantially different would indicate that there aren't omitted variables correlated with sick leave behavior that drive the result as the omitted factors controlled for by the individual fixed effect doesn't affect the estimates.

Challenges to the identification include omitted time trends at the county level that correlate with both reference group mortality and behavior. One candidate may be differential trends in productivity across counties, as individuals in counties with low productivity growth may find it increasingly beneficial to take sick leave relative to counties with high productivity growth. If these productivity trends were correlated with mortality rates it may confound the results. Average labor earnings by county are controlled for to capture such trends.[66]

The mortality shocks used as instruments could capture health shocks that are common to all cohorts. Examples could be a contaminated water supply or pollution from a factory. It may be important to account for health shocks that affect the individual studied as well as his reference group. The results are robust to including the current mortality rate of the individual's own cohort as a control variable, as seen in Table 6.[67,68,69] This control captures local trends that affect the mortality shocks of both the own cohort and the reference group. I am hence controlling for common influences on mortality and only variation in mortality specific to the reference group is used to identify the influence of reference group behavior. The results in Table 6 are very similar to Table 5, indicating that common shocks to mortality across cohorts do not drive the results. Omitted trends that would challenge the identification would not only have to correlate with the reference group's mortality and sick leave across

[66] The results are also robust to controlling for county level fixed effects.

[67] The results are also robust to controlling for the own cohort's mortality rate lagged 3 years (rather than the current rate). In all cases these mortality rates are measured at the county level just like the reference group's mortality rates.

[68] This may be interpreted as relaxing the assumption that the health shocks in (7) are independent across generations and time.

[69] The relatively weak influence of the own cohorts mortality rate in table 6 may seem at odds with the first stage results. However, one may separate the mortality shocks into one part related to sick leave and one part that is unrelated to sick leave. The part that is unrelated to sick leave only produces noise in the estimation, and the results indicate that this noise is cancelled out when averaged across cohorts.

counties, cohorts, and time; the trends would also have to be uncorrelated with the own cohort's mortality rate. Hence, these county level trends would have to differ in a very particular way for generations born a few years apart.

Table 6. Instrumental variable estimates, with control for own cohort's mortality rate.

Dependent Variable: Indicator of positive sick leave benefits
Instrumental variables (2SLS) regressions
Instrument: Mortality per 1000 population for cohorts born 2-4 years earlier by county in year t-3

Reference group	Colleagues: Cohorts born 2-4 years earlier in individual's sector and skill group, living in individual's county				
Time lag	3 years				
Estimator	Pooled	Pooled	Pooled	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Reference group sick leave behavior in year t-3	**0.699**	**0.770**	**0.726**	**0.796**	**0.652**
	(.0913)	(.0858)	(.0786)	(.2107)	(.1792)
Own cohort's mortality rate in year t	**0.0019**	**0.0015**	**0.0018**	**0.0010**	**0.0015**
	(.001)	(.001)	(.0008)	(.0009)	(.0008)
Controls	Yes	Yes	Yes	Yes	Yes
Year trend		Yes			
Year fixed effects			Yes		Yes
Observations	923672	923672	932917	920487	920487

Notes: Controls include age and age sq interacted with gender and education, household composition, marital status, capital income and spousal income, average county earnings, and regional fixed effects.
5 piece splines of lagged income and permanent income included. Splines have knots at quintiles.
Mortality rates computed as number of deaths divided by population by age and county cell.
Individual panel data from 1974-1990, annually. Estimates of the pooled and within estimators.
Standard errors, adjusted for clustering on birth cohort, in parenthesis.
Sample: Labor force participants, 22-60 years old. There are 24 counties.

The instrumental variables approach deals with potential sorting, for example that individuals with a high valuation of leisure could move to places where the non-monetary cost of claiming sick leave benefits is low. First, the individual fixed effect accounts for that individuals differ in their valuation of leisure in unobservable ways wherever they reside. Second, in the within specifications unexplained mortality shocks are used to get exogenous variation in reference group behavior. The mortality shocks are hence positive some years, and for some cohorts, and negative in other periods. Migration flows don't match the patterns of unexplained mortality shocks.

7.2 Neighbors

In this section I turn to an alternative specification of the reference group. The approach is intended to capture the influence of neighbors, who may provide an influence beyond the colleagues studied above. The reference group is defined as those cohorts born 2-4 years earlier who live in the individual's county.[70] The same 3 year time lag is used as above. With the reference group labeled neighbors there is variation across 41 birth cohorts and 24 counties.

Table 7 presents the estimates based on the pooled OLS and within estimators in specifications that mirror Table 4. The pooled OLS estimates are similar with and without a year trend, as well as when year fixed effects are included. The specification in column 4 provides an intermediate step between the pooled and within estimates, incorporating both time varying and time invariant reference group influences.[71] The estimates again indicate that the time invariant influence accounts for at least one third of the reference group influence. The within estimate in column 5 of Table 7 is a bit larger than the estimate based on colleagues. Including the year fixed effects in specification 6 produces a larger estimate of 0.28. It indicates that conditioning on the average national behavior may be important when neighbors are considered as the reference group.

[70] This definition of reference groups have more observations as it is possible to use more years of the sample where sector information is not available.

[71] The first year sick leave behavior is observed is year 1974 for most reference groups, and a later year for a few cohorts that enter the sample after 1977.

Table 7. Reference group behavior (neighbors) and sick leave participation.

Dependent Variable: Indicator of positive sick leave benefits
Linear probability model regressions

Reference group Neighbors: Cohorts born 2-4 years earlier, living in individual's county
Time lag 3 years

Estimator	Pooled	Pooled	Pooled	Pooled	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)	(6)
Reference group sick leave behavior in year t-3	**0.470**	**0.406**	**0.461**	**0.361**	**0.182**	**0.278**
	(.019)	(.021)	(.022)	(.022)	(.019)	(.018)
Reference group sick leave behavior in first year observed				**0.170**		
				(.018)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year trend		Yes				
Year fixed effects			Yes	Yes		Yes
Observations	1510026	1510026	1510026	1510026	1505686	1505686

Notes: Controls include age and age sq interacted with gender and education, household composition, marital status, capital income and spousal income, average county earnings, and regional fixed effects.
5 piece splines of lagged income and permanent income included. Splines have knots at quintiles.
Individual panel data from 1974-1990, annually. Estimates of the pooled and within estimators.
Standard errors, adjusted for clustering on birth cohort, in parenthesis.
Sample: Labor force participants, 22-60 years old. There are 24 counties.

7.2.1 Instrumenting

There may be concerns that the estimates on Table 7 don't capture a causal effect. An instrumental variables approach is applied where the mortality rate for cohorts born 2-4 years earlier who reside in the same county is used to instrument for the reference groups behavior. The groups for which the instrument is computed match the reference groups. Both the pooled and the within models are estimated by 2SLS. The first stage estimates, which are positive as hypothesized, are reported in Table A2. The first stages are not weak.

Table 8. Instrumental variable estimates of reference group influence (neighbors).

Dependent Variable: Indicator of positive sick leave benefits
Instrumental Variable/2SLS regressions
Instrument: Reference group mortality rate per 1000 population by county in year t-3

Reference group Neighbors: Cohorts born 2-4 years earlier, living in individual's county
Time lag 3 years

Estimator Specification	Pooled (1)	Pooled (2)	Pooled (3)	Within (4)	Within (5)
Reference group sick leave behavior in year t-3	**0.813** (.088)	**0.775** (.061)	**0.861** (.071)	**0.785** (.135)	**1.038** (.146)
Controls	Yes	Yes	Yes	Yes	Yes
Year trend		Yes			
Year fixed effects			Yes		Yes
Observations	1510026	1510026	1510026	1505686	1505686

Notes: Controls include age and age sq interacted with gender and education, household composition
marital status, capital income and spousal income, average county earnings, and regional fixed effects
5 piece splines of lagged income and permanent income included. Splines have knots at quintiles.
Mortality rates computed as number of deaths divided by population by age and county cell.
Individual panel data from 1974-1990, annually. Estimates of the pooled and within estimators.
Standard errors, adjusted for clustering on birth cohort, in parenthesis.
Sample: Labor force participants, 22-60 years old. There are 24 counties.

The estimates of the pooled model are about 0.8 as seen in the first three specifications in Table 8. The estimates are a bit higher than the 0.7 estimated in Table 5. The results indicate that the influence of the reference group could be a bit stronger when looking at the broader group of neighbors rather than colleagues, although the confidence intervals overlap. The estimate of 0.79 in the within specification in column 4 in Table 8 is almost exactly the same as in Table 5. The estimate in column 5 of Table 8, where the year fixed effect are included, are higher than the previous estimate and follow the same pattern as without instrumenting in Table 7.[72] The estimates in Table 8 are fairly

[72] The estimated coefficient is now 1.04, although it should not be interpreted literally. A large part of the confidence interval is still below unity. It indicates a very strong influence of reference group behavior when we condition on the national average behavior through the year effect.

similar across specifications.[73] The range 0.75 to 0.78 is within the 95 percent confidence intervals of all the estimates. The similarity between the pooled and within estimates indicates that unobserved fixed characteristics correlated with sick leave behavior have little effect on the estimated effect of reference group behavior when the instrumental variables approach is used.

Table 9. Instrumental variable estimates, with control for own cohort's mortality rate.

Dependent Variable: Indicator of positive sick leave benefits
Instrumental variables (2SLS) regressions
Instrument: Reference group mortality rate per 1000 population by county in year t-3

Reference group: Neighbors: Cohorts born 2-4 years earlier, living in individual's county
Time lag: 3 years

Estimator	Pooled	Pooled	Pooled	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Reference group sick leave behavior in year t-3	**0.769**	**0.746**	**0.845**	**0.758**	**1.019**
	(.084)	(.061)	(.072)	(.138)	(.152)
Own cohort's mortality rate in year t	**0.0019**	**0.0017**	**0.0008**	**0.0014**	**0.0008**
	(.0008)	(.0008)	(.0008)	(.0007)	(.0007)
Controls	Yes	Yes	Yes	Yes	Yes
Year trend		Yes			
Year fixed effects			Yes		Yes
Observations	1510026	1510026	1510026	1505686	1505686

Notes: Controls include age and age sq interacted with gender and education, household composition, marital status, capital income and spousal income, average county earnings, and regional fixed effects.
5 piece splines of lagged income and permanent income included. Splines have knots at quintiles.
Mortality rates computed as number of deaths divided by population by age and county cell.
Individual panel data from 1974-1990, annually. Estimates of the pooled and within estimators.
Standard errors, adjusted for clustering on birth cohort, in parenthesis.
Sample: Labor force participants, 22-60 years old. There are 24 counties.

There may be a concern that the mortality shocks are driven by a factor common to all generations, as discussed above. Including the mortality rate of the own cohort in the county accounts for mortality shocks common across

[73] The results are robust to controlling for county fixed effects.

cohorts. Results are presented when including the current mortality rate of the individual's own cohort in Table 9. Results are very similar if also the mortality rate lagged 3 years is included. The estimates in Table 9 are very similar to Table 8, only slightly smaller in magnitude.

7.3 Robustness: Additional controls, different cohorts and time lags, placebo

To account for individual work habits I have included 4 lags of labor earnings and 4 lags of labor force participation as controls. I have also restricted the sample to individuals who have been in the labor force all of the past 5 years (year t through year t-4). The estimated reference group influence is robust to these alternative specifications, indicating that individual work habits don't affect the estimate of reference group influence.

The results don't rely on the particular reference group or the time lag. I find similar results when the time lag is 1 year or 5 years. The results are also similar if I redefine the reference group to those 2-6 years older, or those 1-3 years older (and these changes are also robust to changing the time lag).[74] As a falsification test I have also estimated a model where I use the 3 year lead of the 2-4 years older cohorts' behavior. The lead should not have an impact on current behavior according to the hypothesis. The estimated effect is insignificant at conventional levels, in line with the hypothesis.[75] In an additional test I create reference groups in a faraway county. I assign the individual a county that corresponds to a faraway county, and match it with the corresponding reference group behavior and instrument. Adding the faraway reference group to the model returns an insignificant estimate on the reference group's behavior in the

[74] I have also estimated a model where the reference group is 2-4 year younger, which would correspond to a model with young 'trend setters'. I find a significant effect, although its significance is much lower than for the model with older reference groups. For this reason I prefer the model with older reference groups.

[75] Note that the lead of the reference group's behavior is the valid 'placebo' treatment in this setting. As individuals may be influenced by several other cohorts it would not be valid to use some different cohorts as placebos. I don't claim that the estimated reference group is the one and only influence. I do claim to find one channel of reference group influence that captures one important intertemporal channel of behavior.

faraway county.

7.4 Interpretations of Reference Group Influence

7.4.1 Psychic cost

I have estimated a significant reference group influence on individual decisions. The theoretical literature has hypothesized that the influence works through a psychic cost, which could be understood as internal or external stigma towards using social insurance benefits (see for example Lindbeck, Nyberg, and Weibull, 1999). The empirical literature has also favored such an interpretation, while recognizing that it is difficult to pin down the exact mechanism (see for example Moffitt 1983 and Bertrand et al 2000). Anthropological studies support the interpretation that the psychic cost of taking sick leave is decreasing with how common it is among colleagues and neighbors (Frykman and Hansen, 2005 and 2009). I believe the interpretation of the reference group influence through reducing the psychic cost is the most attractive.

7.4.2 Health consciousness

Younger generations could have a greater awareness of how their actions affect their health along the lines of Ehrlich and Chuma (1990) and Ehrlich (2000). The young cohorts could hence use sick leave based on a pre-cautionary motive where they invest in their health by taking sick leave.[76] Such behavior could explain at least part of the increasing take up across generations in Figure 2. To the extent this health consciousness differ systematically across cohorts and individuals it is captured by the individual fixed effects in the within regressions. An additional issue is if the health consciousness responds to the mortality shocks for the reference groups (lagged 3 years) used in the regressions above. Such an interpretation is possible. However, it is a bit surprising, from this perspective, that the effect through the reference group is so strong relative to

[76] Ehrlich and Yin (2005) present a quantitative exercise on the importance of such precautionary actions. Sick leave could be a dimension of "life protection" as explored there.

the effect of the own cohort's mortality rate (both the current and past rates), which arguably would have a larger and direct effect on the individual's health consciousness. Yet, with such a health consciousness difference across cohorts it may be expected that the influence of reference group behavior differs across cohorts. I have estimated a model where the reference group influence is allowed to differ between older and younger cohorts. The point estimate for reference group influence is lower for the older cohorts compared to the younger cohorts but the difference is not significant. While the point estimates are consistent with this interpretation, the evidence does not support significant differences in reference group influence across cohorts.

7.4.3 Monitoring

It could be possible that different generations are subject to different monitoring or punishment. If older generations are punished more severely for using the sick leave program it could lead to lower take up among these generations. Employers would be the ones delivering the punishments since the monitoring by the social insurance administration is basically non-existent during the period. Any systematic differences across individuals would be captured by the individual fixed effects. The remaining concern is that monitoring would covary with reference group behavior and mortality rates across individual life cycles. Given that the reference group's mortality rate is lagged three years there is no obvious reason to expect the current monitoring of the own cohort to depend on these factors, in particular since the own cohort's mortality shocks are controlled for. However, if such differences exist they may be expected to differ by sector. Private profit maximizing firms may have a stronger incentive to punish potential shirkers compared to public sector employers. Estimating the model for public and private employees separately do not reveal any significant differences between the reference groups influences, indicating that differential monitoring across generations does not affect the estimated effects.

Colleagues could be monitors. One way this could work is that there are few colleagues around to monitor if they are on sick leave themselves, but it is not clear that their absence three years ago would have an effect on current sick leave. Another channel is if a larger absence among colleagues would make the individual care less about any potential punishment from the colleagues, but this channel would be one example of the non-monetary cost hypothesized in the model above and hence fit well with the main interpretation of the results.

7.5 Taking Stock

Reference group behavior, as shifted by mortality shocks, has a direct influence on individual sick leave decisions. The identifying assumption is that there aren't omitted local trends that correlate with reference group mortality and behavior but are uncorrelated with the mortality of those a couple of years younger. I may entertain stories that there are local trends in for example drug abuse (or pollution) that affect both sick leave and mortality. Such trends could potentially challenge the identification since both reference group sick leave and mortality as well as individual sick leave could be affected by the same drug abuse trend. It is reassuring that the influence of role model behavior is robust to including the own cohort's mortality rate, as the own group's mortality would capture the drug abuse trend.[77] Using reference group mortality as an instrumental variable, and controlling for the mortality of the individual's own cohort, makes a compelling case that one channel of intertemporal influence in sick leave choices has been identified.

8 Conclusion

This is the first paper to estimate the long-run dynamic adaptation of individual behavior in the welfare state. Although the underlying mechanism I model

[77] If the drug abuse trend did not affect mortality it would not be a challenge in the first place since it would be uncorrelated with reference group mortality, and hence not part of the variation used to identify the estimate.

has been discussed in several literatures[78] few papers *empirically* evaluate how institutions and economic outcomes affect preferences over time. While many have shown how institutions shape outcomes across locations little evidence exists on how different outcomes come about.

I provide evidence on how norms evolve and affect behavior using a large individual panel data set. Variation across generations and over time within individuals is used to estimate a model where the benefit take up decision depends on the past behavior of role models.[79] I find that being exposed to older generations that used the sick leave program more is associated with higher individual demand for benefits. This mechanism can account for a majority of the behavioral differences across cohorts. Mortality rates are used to instrument for reference group behavior to address concerns that omitted variables, such as local health or productivity trends, may drive the results. The instrumented results point to a strong and robust intertemporal influence of reference group behavior on individual decisions.

The adaptation mechanism I estimate could apply to other welfare state programs and in other settings.[80] The findings, that younger generations use social insurance more than the older generations, correspond with survey evidence on attitudes towards claiming public benefits among the young. Younger generations have a higher acceptance of claiming public benefits one is not entitled to according to the World Values Survey.[81] This is a consistent finding across countries, not only Sweden, indicating that the intertemporal mechanism I estimate could be at work elsewhere.[82]

Furthermore, social insurance programs may influence family formation and fertility as studied by Ehrlich and Zhong (1998) and Ehrlich and Kim (2007).

[78] The program participation literature talks about stigma affecting choices. The literature on culture asks how beliefs affect economic outcomes, see for example Bisin and Verdier (2010) and Fernandez (2010). Doepke and Zilibotti (2008) model the evolution of work norms.

[79] Preferences are modeled such that the threshold for claiming benefits depends on your experience with role model behavior.

[80] The intertemporal mechanism does not depend on the particulars of the program.

[81] The wording of the question is 'Do you think it can always be justified, never be justified, or something in between, to claim government benefits to which you are not entitled.'

[82] This pattern is robust to controlling for gender, education, employment status, marital status, income, country fixed effects, and survey wave effects. See Ljunge (2011) for details.

Attitudes toward benefit use is transmitted across generations to altruistic attitudes as analyzed in Ljunge (2012a). The changing demand for benefits across generations and time studied in this paper could hence influence other margins, which in turn could induce further adjustments over time. Moreover, the increasing demand for social insurance I find indicates a challenge to the sustainability of social insurance programs over and above an aging population and globalization.

Policy reform does not take place in a static environment. Behavior adapts over time even though policies remain constant. My analysis suggests that behavioral responses to the provision of welfare state benefits estimated by natural experiments are likely to strongly underestimate the true long-run elasticities relevant for the fiscal sustainability of the welfare state.

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9 Appendix

Table A1. First stage regressions (colleagues).

First stage results corresponding to Table 5.
Dependent Variable: Reference group sick leave
Reference group: Cohorts born 2-4 years earlier in individual's sector and skill group, living in individual's county

Estimator	Pooled	Pooled	Pooled	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Mortality rate per 1000 population in cohorts 2-4 years older by county	**0.020**	**0.021**	**0.021**	**0.007**	**0.007**
	(.0025)	(.0026)	(.0026)	(.0014)	(.0014)
Controls	Yes	Yes	Yes	Yes	Yes
Year trend		Yes			
Year fixed effects			Yes		Yes
Observations	932917	932917	932917	928312	928312

Notes: Controls include age and age sq interacted with gender and education, household composition, marital status, capital income and spousal income, average county earnings, and regional fixed effects.
5 piece splines of lagged income and permanent income included. Splines have knots at quintiles.
Mortality rates computed as number of deaths divided by population by age and county cell.
Individual panel data from 1979-1990, annually. Estimates of the pooled and within estimators.
Standard errors, adjusted for clustering on birth cohort, in parenthesis.
Sample: Labor force participants, 22-60 years old. There are 24 counties.

Table A2. First stage regressions (neighbors).

First stage results corresponding to Table 8.
Dependent Variable: Reference group sick leave
Reference group: Cohorts born 2-4 years earlier living in individual's county

Estimator	Pooled	Pooled	Pooled	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Mortality rate per 1000 population in cohorts 2-4 years older by county	**0.016**	**0.022**	**0.020**	**0.010**	**0.008**
	(.0024)	(.0023)	(.0023)	(.0015)	(.0014)
Controls	Yes	Yes	Yes	Yes	Yes
Year trend		Yes			
Year fixed effects			Yes		Yes
Observations	1510026	1510026	1510026	1505686	1505686

Notes: Controls include age and age sq interacted with gender and education, household composition, marital status, capital income and spousal income, average county earnings, and regional fixed effects.
5 piece splines of lagged income and permanent income included. Splines have knots at quintiles.
Mortality rates computed as number of deaths divided by population by age and county cell.
Individual panel data from 1979-1990, annually. Estimates of the pooled and within estimators.
Standard errors, adjusted for clustering on birth cohort, in parenthesis.
Sample: Labor force participants, 22-60 years old. There are 24 counties.