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

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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. The influence of older generations' behavior remains when instrumenting using mortality rates, which makes a compelling case for a causal intertemporal influence on individual demand.

JEL codes: H31, I18, J22, Z13

Key words: social insurance, adaptation, role models

1 Introduction

I study the adaptation of demand for benefits following an expansion of welfare state institutions, and estimate the speed at which rational agents adapt to new social conditions in a simple model used by theorists. I estimate a model that allows for preferences to adapt to aggregate behavior, in effect allowing social norms to adjust to observed behavior. I find substantial long run adaptation with regard to the demand for welfare state benefits, an increase of one percentage point in benefit take up per birth cohort.

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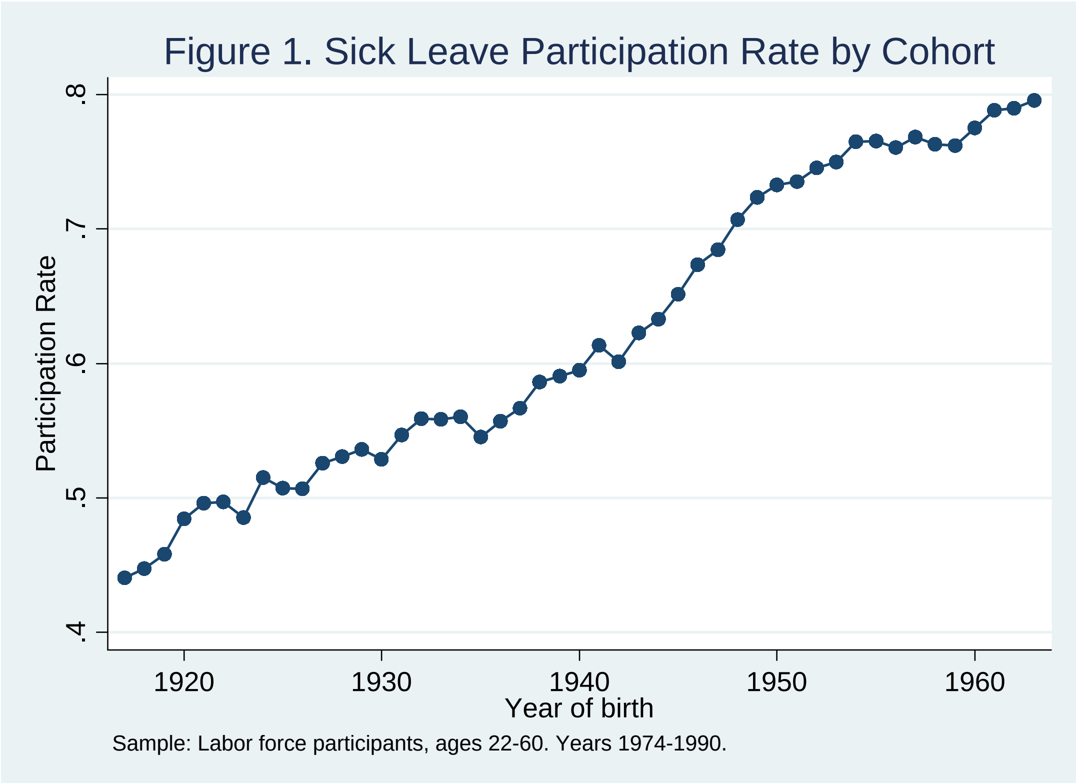


Young generations have much higher take up rates compared to those born earlier. The pronounced increase across generations in the take up of sick leave benefits occurred while program rules remained constant.[1] As shown in Figure 1, the generation born in 1919 has an average take up rate of 45 percent, 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. I account for a large number of factors that could influence benefit take up and potentially explain the cohort trend, yet, this trend persists. Figure 1 suggests that behavior has adapted significantly

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

[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.

in the face of constant institutions, consistent with theoretical analyses about changes in work norms in the welfare state.

The analysis contributes to a primarily theoretical literature on long term dynamics. The model is closely related to the evolution of work norms modeled in Lindbeck, Nyberg, and Weibull (2003) and Doepke and Zilibotti (2008). Quantifying the size of this adjustment and estimating a particular mechanism through which this adjustment takes place is an empirical question that to my knowledge this paper is the first to provide an answer to.

I write down an empirical model of program participation that includes a psychic cost for claiming benefits.[3] I estimate a psychic cost function and quantify how the past behavior of older cohorts influences individual behavior. The estimated model can account for half of the increased demand across generations.

The psychic cost modeled, which operates on the demand for benefits, would apply to any social insurance program. I focus on the take up of sick leave benefits in Sweden. What makes the program particularly suited for study is the lack of supply side constraints. Behavior reveals demand without any supply interference, as claiming some benefits is completely at the individual's discretion.

I estimate the importance of the psychic cost versus a general shift over time towards more social insurance take up. I apply an instrumental variables approach to identify the intertemporal influence of older cohorts. Mortality rates are used as an instrument for the older cohorts' sick leave behavior. This approach isolates the influence of the older generations' behavior to the part that is shifted due to unexplained mortality shocks. The influence of the older cohorts' behavior remains strong. The result is robust to controlling for mortality shocks that are common across cohorts, hence using only the variation in mortality shocks specific to the reference group. The analysis makes a compelling case that the estimated intertemporal influence in the demand for social

[3] The term psychic cost is used to describe the mechanism. What is modeled and estimated is the influence of reference group behavior. This may be, internal or external, stigma or some other effect that is captured by the reference group's behavior such as social learning.

insurance is causal. This provides unique evidence on how individuals adapt to institutions.

The dynamic model estimated 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.[4] 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.[5] I study intertemporal differences, across generations and within life cycles, to examine how individuals adapt to social conditions.

The paper is organized as follows. The next section discusses the related 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 psychic cost are modeled, but it is also close to Lindbeck, Nyberg, and Weibull (1999). Other models with delayed responses are the intergenerational transmission of traits or work norms by Doepke and Zilibotti (2008), Bisin and Verdier (2001, 2004), Lindbeck and Nyberg (2006), and Tabellini (2008). I examine the influence of role models across generations rather than the link between parents and children. Empirical applications include transmission of

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

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

work norms from parents to children (Fernandez, Fogli, and Olivetti, 2004; Lindbeck and Nyberg, 2006). The analysis is also related to the dynamics of the welfare state in Hassler, Mora, Storesletten, and Zilibotti (2003).

Fogli and Veldkamp (2010) study the evolution of female labor force participation. They write down a model of social learning similar to Fernandez (2008). 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.[6] 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.[7] Aghion, Algan, Cahuc, and Shleifer (2010) argue that trust affects regulation, based on a cross-country analysis. Algan and Cahuc (2010) use a model of intergenerational transmission of beliefs to examine the effect of trust on per capita income. Luttmer and Singhal (2011) find evidence that cultural background, as well as current factors, affect attitudes towards redistribution. My paper complements the literature by studying dynamics of norms within one country. 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

[6] See the handbook edited by Benhabib, Bisin, and Jackson (2010).
[7] The mechanism is similar to what Beaman, Chattopadhyay, Duflo, Pande, and Topalova (2009) explore in the sense that exposure affects preferences, which in turn affect actions.

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).[8] The effects of social norms have been studied in the context of unemployment insurance, a related social insurance program, see Bruegger, Lalive, and Zweimueller (2010), Stutzer and Lalive (2004), and Clark (2003). None of these studies of social interactions have analyzed the intertemporal adaptation process, which I do.

The program participation literature casts the take up decision as a trade off between time and consumption. Another way to view the sick leave decision is as an expression of well-being, which ties in with the literature on self reported well-being.[9] What I have labeled a psychic cost may be seen as a relative or positional concern in the language of the well-being literature. This literature builds on a model where the relative position has a contemporaneous effect on well-being, for example Luttmer (2005) finds that individuals who have neighbors with higher income have lower well-being, while controlling for own income and characteristics as well as neighborhood factors.[10] That is, they assume an immediate cross-sectional, usually spatial, effect of the reference group's income/consumption on your well-being. The model in this paper focuses on an intergenerational link the existing empirical literature has not entertained.[11]

[8] Two papers on the social interactions in the use of sick leave in Sweden are Hesselius, Johansson, and Vikström (2009) and Lindbeck, Palme, and Persson (2008). Both papers focus on contemporaneous spatial interactions, not the intertemporal link I focus on. Henrekson and Persson (2004) studies sick leave in Sweden in a long aggregate time series, but they make no intergenerational links.

[9] Graham (2009) finds that health is the strongest correlate with self reported well-being in a large cross section of countries. Daly and Wilson (2009) study suicides as a manifestation of low subjective well-being, which is similar to the argument regarding sick leave.

[10] Additional evidence that well-being is partly driven by relative position are Clark and Oswald (1996), Blanchflower and Oswald (2004), Ferrer-i-Carbonell (2005), Kingdon and Knight (2007), and Clark, Kristensen, and Westergård-Nielsen (2008).

[11] Furthermore, all these papers use self-reported survey measures of well-being, which has short comings as discussed by Bertrand and Mullainathan (2001) and Ravallion and Lokshin (2001). The measure of well-being in this paper, sick leave, is based on actions, which overcomes shortcomings of the previous literature.

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.[12] 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.[13] 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.[14] 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.

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.[15] 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

[12] 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.

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

[14] Since we analyze the extensive margin, the validation by the physician is not relevant in our study.

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

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.[16]

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).[17] I follow a random sample of the 1974 population for 17 years. The baseline regression has just short of 2 million observations based on the behavior of about 160,000 individuals. Birth cohorts from 1917 to 1963 are included. About 3 percent of the population is sampled.[18] 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 de-

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

[17] 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.

[18] 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).

fined 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 participants.[19] Summary statistics are presented in Table 1.

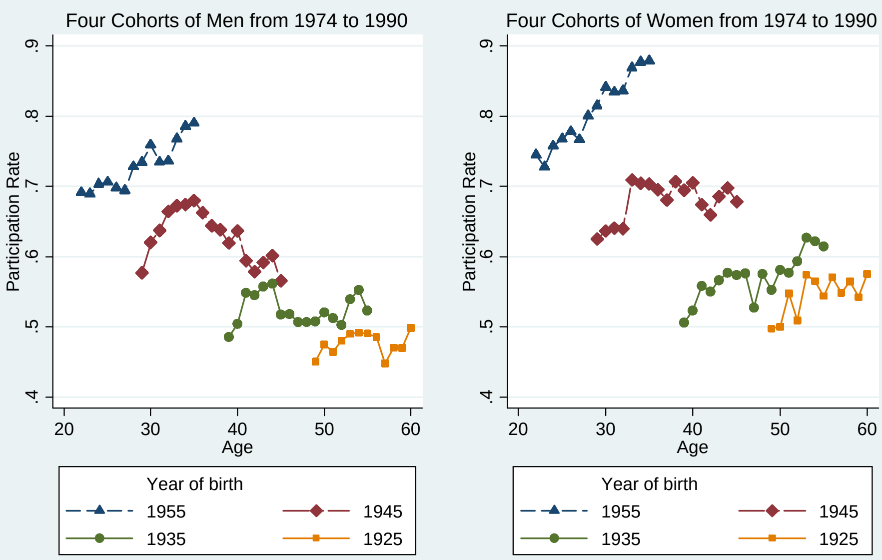
[19] Labor force participation is defined as having positive labor earnings during the year.

5 Increased Demand For Social Insurance

5.1 Aggregate Trends

It is possible the raw averages in Figure 1 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.[20] Figure 2 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.[21]

Figure 2. Sick Leave Participation for Men and Women.



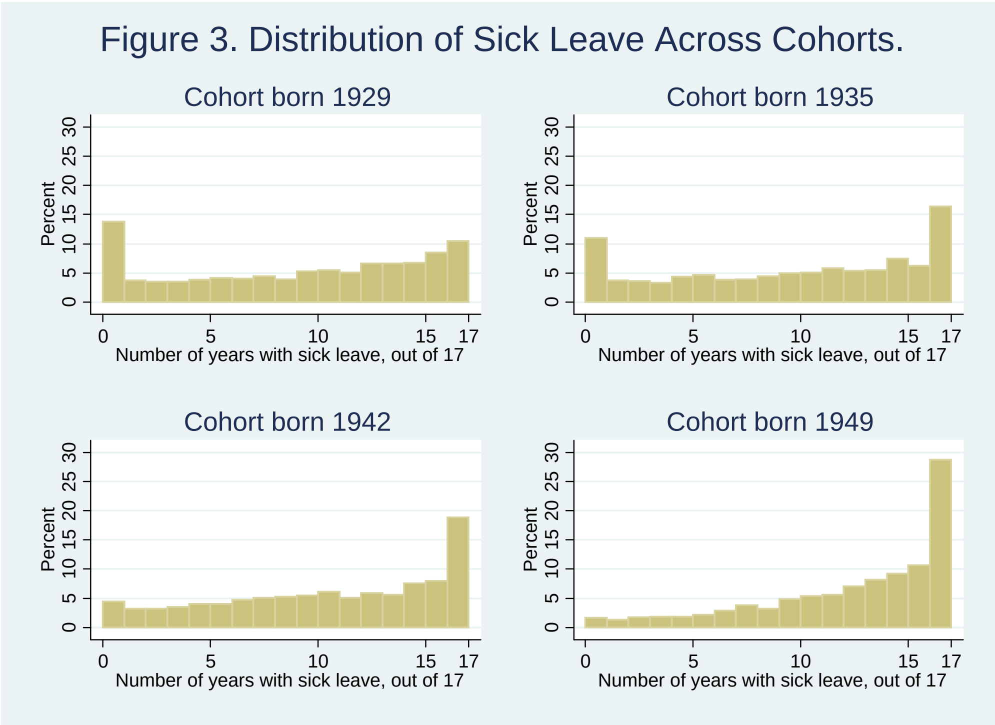
Sample: Labor force participants, ages 22-60.

There may be concerns that changes in labor force participation are behind

[20] 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.

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

the increasing sick leave take up across generations.[22] 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 3. The figure plots the distribution of how often individuals use the sick leave program across cohorts.[23] For the oldest cohort

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

[23] For each individual I've computed the number of years of sick leave participation when

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 2. I include a full set of interactions between gender, the four education groups,[24] 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. 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

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.

[24] 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.

may be jointly determined. I also control for regional business cycles (through the regional employment rate) and regional fixed effects.[25] 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.

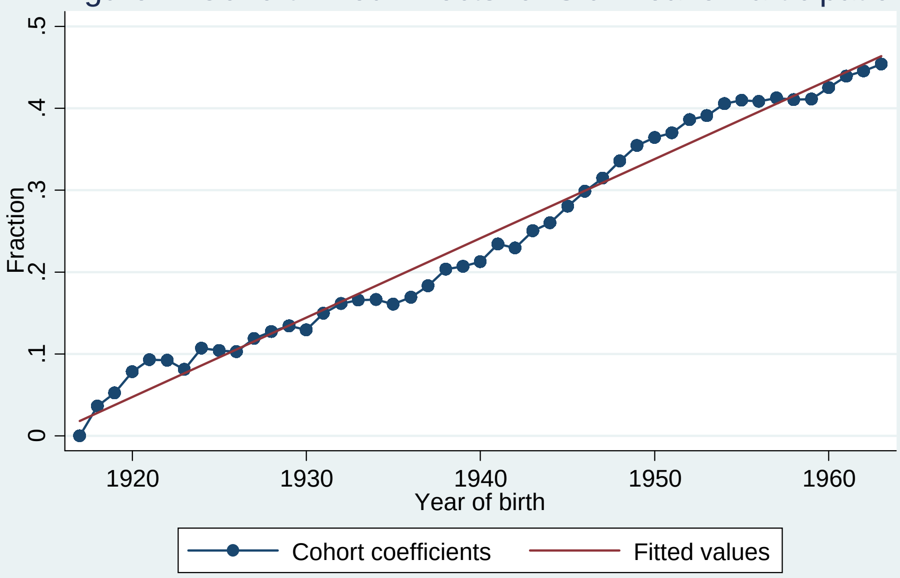
It is possible that not only current earnings but lifetime earnings affect the sick leave choice. Using the panel data, I run an individual fixed effect (within)

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

regression of individual earnings on the age-gender-education interactions mentioned above and business cycle controls. The individual fixed effect from that 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.[26] 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.

Figure 4. Cohort Fixed Effects for Sick Leave Participation



Note: Estimated cohort effects after controlling for demographics, income, etc.

[26] The results are robust to using 10-piece splines.

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 3.[27] 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 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

[27] Being born in 1917 is the omitted category.

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.[28]

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.[29, 30]

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.[31]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

[28]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.

[29]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.

[30]The cohort trend is also robust to controlling for tax rates. Ljunge (2011) 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.

[31]Another compositional story would relate 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.

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 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: Specification	Program definition (1)	Use of other programs (2)	Labor force composition 1 (3)	Labor force composition 2 (4)	Secular drift (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
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. 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.

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.[32] 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.[33]

6 A Mechanism: Reference Group Influence

The psychic cost attached to claiming social insurance benefits (Moffitt 1981) may depend on the behavior of other individuals in the economy. In particular, following Lindbeck, Nyberg, and Weibull (2003), psychic cost may not adjust instantaneously to behavior in the reference group but with a lag. The more common it is to claim social insurance benefits, the lower is the psychic cost. With the psychic cost adjusting slowly, behavior may adjust for a long time before reaching a steady state. The higher social insurance take up of younger generations is interpreted within the structure of a model.

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.[34] If benefits are claimed the worker consumes a fraction ρ of his earnings (ρ represents the replacement

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

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

[34] 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.

rate), enjoys some extra leisure, and suffers psychic cost γ. The preferences of individuals are represented by

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

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.[35] The random shock ε affects the value of taking up the social insurance benefit. ε is assumed to be distributed i.i.d. (across individuals and time) with mean zero according to cumulative distribution function Ψ with positive density on the whole real line. 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, conditional on ε, by $\beta^*_\varepsilon = -\ln \rho + \gamma - \varepsilon$. By integrating out the idiosyncratic component the cut off value in the population is obtained, which may be expressed as

$$\beta^* = \int [-\ln \rho + \gamma - \varepsilon] \, d\Psi(\varepsilon) = -\ln \rho + \gamma \tag{2}$$

The take up rate of the social insurance benefit in the economy, call it z, corresponds to the fraction with $\beta > \beta^*$, that is,

$$z = 1 - \Phi(\beta^*) \tag{3}$$

The current psychic cost depends on the share of transfer recipients in group m in the previous time period; $\gamma_t = h(z_{m,t-1})$.[36] Furthermore, $h : [0,1] \to \mathbb{R}_+$ and h is continuously differentiable with $h' \leq 0$.

Individuals take prices, preference parameters, and $z_{m,t-1}$, and hence the psychic cost, as given. The equilibrium outcome in period t is a take up rate for

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

[36] The psychic 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.

each group n, $z_{n,t}$, who is influenced by past behavior of group m, such that

$$z_{n,t} = 1 - \Phi\left[-\ln\rho + h\left(z_{m,t-1}\right)\right]. \tag{4}$$

In a steady state (4) holds for any n, m, t.

I assume that the parametric specification for the psychic cost is

$$h\left(z_{m,t-1}\right) = s_0 - sz_{m,t-1} \tag{5}$$

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 $-\ln\rho + \beta - s_0 + sz_{m,t-1} - \varepsilon > 0$. 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

$$SL^*_{i,n,t} = \alpha + x_{i,t}\delta + sz_{m,t-1} - \epsilon_{i,t} \tag{6}$$

$$SL_{i,n,t} = \begin{cases} 1 & \text{if } SL^*_{i,n,t} \geq 0 \\ 0 & \text{if } SL^*_{i,n,t} < 0 \end{cases} \tag{7}$$

α captures all constant parts of the model. It is possible to recover the slope coefficient in (5) from the data. 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 1 as would happen in a standard adoption model, see for example Fernandez (2008).[37] These models do, however produce a long straight segment just like in Figure 1. 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

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

cohorts from the early 1950's are above the regression line in Figure 4 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.

6.2 Reference groups

The groups are intended to capture 'synthetic colleagues,' as the most direct influence may be from colleagues who share the same professional characteristics.[38] Individuals who are a few years older and a bit ahead in the career may serve as role models for the individual's current decision. The role models could set a standard for acceptable behavior.[39] 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 psychic cost to be affected by the fraction of the reference group that takes up the social insurance benefits.[40] 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 in the

[38] 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.

[39] Such mechanisms have been discussed in the developmental psychology literature, see for example Harris (1995, 1998). There is also evidence that individuals are affect by people in their environment, see for example Bertrand et al (2000) and others discussed above.

[40] 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.'

same education and sector group living in the same county.[41] The time lag is 3 years.[42] The adjustment of psychic cost 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 psychic 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, the intergenerational spillover that is essential in the model to explain the behavior across generations in Figure 1.[43]

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 on the control variables) the slope parameter in the psychic cost function (5)

[41] 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.

[42] 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.

[43] 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.

is estimated, which has a structural interpretation. This would provide a clear insight for policy design by quantifying the 'rings on the water' 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 the psychic cost, which induce other individuals to take up the benefits, and so on.[44]

If the real world is more complex than the model then the interpretation of the estimates may change. It is possible that the true psychic cost is unobserved, that is, the psychic cost is an omitted variable like attitudes and beliefs of the reference group that in turn affect individual behavior.[45] Reference group behavior may then capture these attitudes and beliefs, but the estimated slope parameter in (5) would not have a structural interpretation if the psychic 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.[46] The estimates from the two methods have distinct interpretations, which are explored. The first three specifications use the pooled OLS estimator.[47] The estimate on the reference group behavior is to a large extent identified from variation across individuals. The reference groups are based on the measure of colleagues, which exhibit variation across 41 birth cohorts, 4 skill-sector groups, and 24 counties. The coefficient on reference group behavior is positive

[44] The intergenerational mechanism has the potential of explaining the pattern in figure 1, in contrast to a purely spatial mechanism since generations are not systematically separated spatially.

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

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

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

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 psychic cost (s in the model).

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	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Reference group sick leave behavior in year t-3	**0.468**	**0.457**	**0.458**	**0.123**	**0.124**
	(.016)	(.016)	(.016)	(.01)	(.01)
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. 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.

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 only picking up some unobserved characteristic of individuals that differs across generations I estimate the model accounting for unobserved fixed characteristics using the within estimator. In the within case the estimate is identified from variation in reference group behavior within the same individual.[48] The individual fixed effect would capture any influence of work norms instilled by parents. A significant estimate of reference group behavior would support the presence of time varying influences, that there is an influence of the psychic 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 4 in Table 4, and the estimate is strongly significant.[49]

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.[50] Again, the coefficient estimate on the 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

[48] 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.

[49] 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.

[50] 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.

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.[51]

Including year fixed effects in the within estimator alters the interpretation on the estimated coefficient of reference group behavior.[52] 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 5 of Table 4 indicates that the influence of reference group behavior conditional on national behavior is similar to not conditioning on national behavior.[53]

7.1.1 Instrumenting for reference group behavior

To further examine the hypothesis an instrument is used to get exogenous shifts in sick leave behavior of the reference group. I use mortality rates corresponding to the cohorts and locations of the reference groups to instrument for reference group behavior.[54] 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.[55] 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.

[51] 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.

[52] 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.

[53] The estimate in specification (5) is not directly comparable to specification (3) since the pooled estimate does not have a similar double difference interpretation.

[54] 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.

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

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

$$MR_{c,g,t} = \alpha_0 + \alpha_1 Age_t + \alpha_2 Age_t^2 + \varepsilon_{c,g,t} \quad (8)$$

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[56] 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 and education-sector group, lagged 3 years.[57] 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.[58]

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

[56] 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.

[57] 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.

[58] More formally, the assumption is that the mortality shocks in (8) 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 (6).

up take as hypothesized. The instrument is not weak.[59] The first stage results are reported in Table A1 in the appendix.

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.

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.[60] With year fixed effects the estimated coefficient is 0.66,

[59] 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.

[60] The demographic interactions can be seen as controlling for learning over the life cycle,

as seen in specification 5 in Table 5.

Overall, the estimated influence of role model behavior is larger when instrumenting with mortality rates.[61] 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 psychic 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 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.[62]

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

where the learning follows a second order polynomial for each of the demographic groups.

[61] 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.

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

a control variable, as seen in Table 6.[63,64,65] 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 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.

The instrumental variables approach deals with potential sorting, for example that individuals with a high valuation of leisure could move to places where the psychic 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.

[63] 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.

[64] This may be interpreted as relaxing the assumption that the health shocks in (8) are independent across generations and time.

[65] 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.

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.

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 individuals county.[66] 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.

[66] 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.

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 within estimate in column 4 of Table 7 is a bit larger than the estimate based on colleagues. Including the year fixed effects in specification 5 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.

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	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Reference group sick leave behavior in year t-3	**0.470**	**0.406**	**0.461**	**0.182**	**0.278**
	(.019)	(.021)	(.022)	(.019)	(.018)
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. 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	Pooled	Pooled	Pooled	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Reference group sick leave behavior in year t-3	**0.813**	**0.775**	**0.861**	**0.785**	**1.038**
	(.088)	(.061)	(.071)	(.135)	(.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.[67] The estimates in Table 8 are fairly similar across specifications.[68] 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.

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 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.

[67] 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.

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

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.

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).[69] 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.[70]

7.4 Alternative Interpretations

7.4.1 Health consciousness

Younger generations could have a greater awareness of how their actions affect their health along the lines of Ehrlich (1990, 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. Such behavior could explain at least part of the increasing take up across generations in Figure 1. To the extent this health consciousness differ systematically across cohorts and individuals it is captured by the individual fixed effects in the within regressions. A remaining concern would be if the health consciousness responds to the mortality shocks for the reference groups (lagged 3 years) used in the regressions above. Although such an interpretation is possible, it does not seem as the most likely explanation since the results are robust to controlling for 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, if there is such a health consciousness difference across cohorts it may be expected that the influence of

[69] 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.

[70] 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 that we find one channel of reference group influence that captures one important intertemporal channel of behavior.

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. The evidence does not seem to support such differences across cohorts.

7.4.2 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 psychic cost hypothesized in the model above and hence fit well with the main interpretation of the results.

7.5 Taking Stock

Taken together, I believe the analysis builds a strong case for causality; that 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.[71] 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

How do individuals adapt to institutions? Plenty of evidence show that institutions shape different outcomes across locations.[72] However, precious little evidence exists on how these outcomes come about. It is known that societies and communities end up with different outcomes based on the institutions they face or faced, but very little is known about how they got there.

I model a preference mechanism that can explain the dramatic increase in demand for sick leave across cohorts in Sweden. Individuals' benefit take up

[71] 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.

[72] See for example Bisin and Verdier (2010), Fernandez (2010), and Tabellini (2008b).

decision is allowed to depend on the behavior of 'role models.'[73] I estimate the model and it can account for a majority of observed behavioral differences across cohorts. This is the first paper to estimate the long-run dynamic adaptation of individual behavior in the welfare state. The underlying mechanism studied is present in several literatures.[74] Yet, few papers *empirically* evaluate how institutions and economic outcomes affect preferences over time.

I provide evidence on how norms evolve and how they affect behavior using a large individual panel data set. Variation across different generations as well as variation over time within individuals is used to estimate a model where the take up decisions depend on the past behavior of role models. I find that being exposed to older generations that used the sick leave program more is associated with higher individual demand for the program. 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. Variation in reference group behavior due to unexplained mortality shocks have a substantial impact on individual decisions to take up sick leave. The instrumented results point to a strong and robust intertemporal influence of reference group behavior on individual decisions.

I focus on the take up of sick leave benefits in Sweden, since this decision is purely determined by individual demand. Individuals assess themselves if they are unfit to work and want to collect sick leave benefits. Changing behavior can be seen as an estimate of how the self-assessed threshold for claiming benefits change. The specifics of the program lend it to study of the intertemporal mechanism modeled, but the mechanism and the results are quite general. The intertemporal mechanism does not preclude that for example spatial interactions are present or that there are additional intertemporal mechanisms. The model captures a quantitatively significant mechanism, and the instrumented results

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

[74] The program participation literature talks about stigma affecting choices. The literature on culture asks how beliefs affect economic outcomes. Doepke and Zilibotti (2008) model the evolution of work norms.

provide compelling evidence that the intertemporal mechanism is indeed one channel of influence on individual decisions.

The estimated intertemporal adaptation mechanism may apply to all kinds of welfare state programs. 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.[75] This is a consistent finding across countries, including Sweden, and indicates that the intertemporal mechanism at work in Sweden could be relevant elsewhere.[76] The model could apply to other social insurance programs with different levels of generosity as the intertemporal mechanism does not depend on the generosity or particulars of the program.

Being exposed to welfare state institutions may have a profound effect on individuals' behavior. The increasing take up rates of benefits across cohorts in Figure 1 plainly show that a substantial shift in society is in progress. I postulate and estimate a particular mechanism to explain the trend. Experience with role models who demand more social insurance result in higher individual demand, both when compared across generations and along the life cycle path within generations. The analysis indicates that large policy reforms don't take place in a static environment. Preferences for program benefits may not be fixed. Individuals gradually adapt to the environment and demand more benefits. For generations born a few decades apart this adds up to a fundamental shift in behavior where the young have much higher demands on public programs. Quantifying the adaptation process to the public policy, and estimating a specific mechanism using a new empirical strategy are this paper's unique contributions.

[75] 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.'

[76] This pattern is robust to controlling for gender, education, employment status, marital status, income, country fixed effects, and survey wave effects.

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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	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.