Sick of the Welfare State? Adaptation in the Demand for Social Insurance

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November 22, 2010

Abstract

We argue that the supply of social insurance programs has long term effects on individual demand for program benefits. We postulate a model where the utility of taking up social insurance benefits depends on older generations' past behavior, and we estimate the model using individual panel data. This intertemporal mechanism can account for three-quarters of the younger generations' higher demand for social insurance benefits. The influence of older generations' behavior remains when we instrument using mortality rates.

JEL codes: H31, I18, J22, Z13

Key words: social insurance, adaptation, norm dynamics, role models

1 Introduction

We study the dynamic adaptation of behavior in the welfare state. We find substantial long run adaptation with regard to demand for welfare state benefits. More specifically, we find an almost 1 percentage point increase in the benefit take up per birth cohort. We estimate a structural model that allows for preferences to adapt to aggregate behavior, in effect allowing social norms to adjust to observed behavior. The dynamic model we estimate 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

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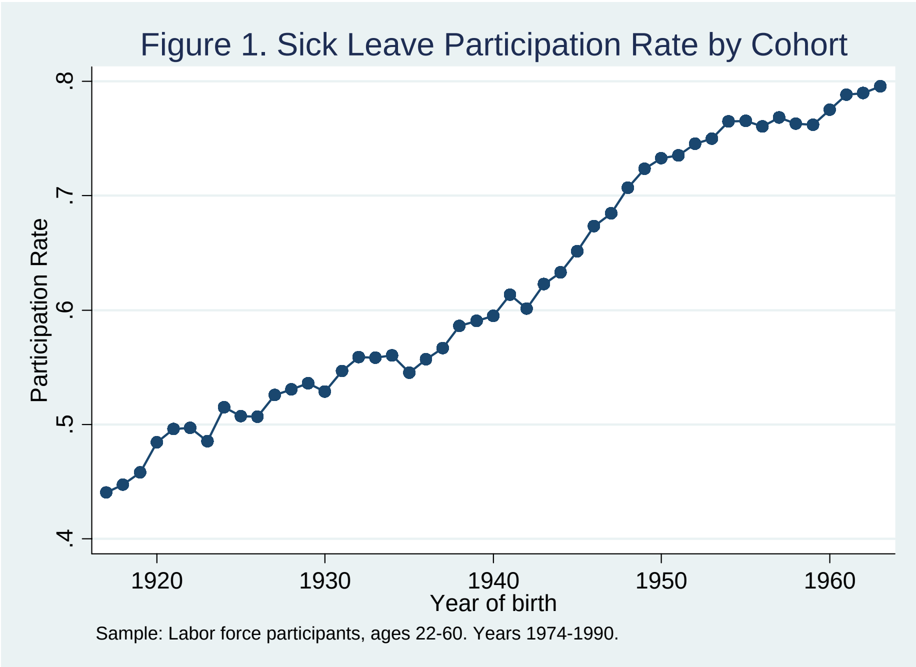
new equilibrium.[1] We study the adaptation process following the expansion of welfare state institutions, and estimate the speed at which rational agents adapt to the social conditions in a simple structural model used by theorists.[2]



There is a pronounced increase across generations in the take up of sick leave benefits in Sweden, although program rules have been constant.[3] Young generations have much higher take up rates compared to those born earlier. 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.[4] Each younger birth cohort has a take up rate that is almost

[1] See Bisin and Verdier (2010) for a survey.
[2] The related literature is discussed in detail in the next section.
[3] Take up is defined as receiving some (that is, at least one day of) benefits during the year.
[4] We observe older generations later in their life cycle when their health may be worse, so we might have expected to see higher take up rates for older generations compared to the young.

1 percentage point higher than those born one year earlier. We account for a large number of factors that could influence benefit take up and potentially explain the cohort trend. Yet, this trend persists.

Our analysis contributes to a primarily theoretical literature on long term dynamics. Our model builds most closely on Lindbeck, Nyberg, and Weibull (1999, 2003), but it is also closely related to the evolution of work norms modeled in Doepke and Zilibotti (2008) as well as the dynamics of the welfare state in Hassler, Mora, Storesletten, and Zilibotti (2003). While theorists have hypothesized about changes in work norms in the welfare state, the aggregate data we present suggests that behavior has adapted significantly in the face of constant institutions. Quantifying the size of this adjustment and estimating a particular mechanism through which this adjustment takes place is an empirical question that to our knowledge we are the first to provide an answer to.

The social interactions literature is different as it usually assumes an immediate adaptation to some social influence, or as in the studies of the long term effects of institutions, that the adaptation process has reached a new stationary equilibrium. The argument is that different social conditions, either contemporaneous or historical, have resulted in different stationary equilibria across different locations, but how these equilibria are reached is a black box. We are different in that we study the adaptation process before it reaches a stationary state. Our 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] We study intertemporal differences, across generations and within life cycles, to examine how individuals adapt to social conditions.

The psychic cost we model, which operates on the demand for benefits, would apply to any social insurance program.[6] We focus on the take up of sick leave

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

[6] We use the word psychic cost to describe the mechanism. What we model and estimate 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.

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.

We write down an empirical model of program participation that includes a psychic cost for claiming benefits, based on Lindbeck, Nyberg, and Weibull (2003). We estimate a psychic cost function and quantify how older cohorts' past behavior influences individual behavior. The estimated model can account for three-quarters of the increased demand across generations.

We estimate the importance of the psychic cost versus a general shift over time towards more social insurance take up. We are also able to quantify the importance of factors that are constant within an individual versus the importance of the psychic cost that varies over time. This provides a quantification of the relative importance of time varying social influences compared to culture. Culture is considered the slow moving part of preferences,[7] for example the work norms instilled by your parents.

We apply an instrumental variables approach to identify the intertemporal influence of older cohorts. We use mortality rates 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 by the mortality shocks, and the estimator isn't affected by fixed factors like culture. The influence of the older cohorts' behavior remains strong.

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 we develop our empirical model and we present the empirical results. Section 7 concludes.

[7] This distinction between time varying social influence and culture is discussed in Guiso, Sapienza, and Zingales (2006).

2 Related Literature

Our study of long term adjustments in demand for social insurance, where we follow individual behavior across decades, complements several existing literatures. The effect of norms on labor supply (or benefit up take) has been studied both theoretically and empirically. Our model is most closely related to Lindbeck, Nyberg, and Weibull (2003) in how we model individual heterogeneity and the psychic cost, 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), Lindbeck and Nyberg (2006), and Tabellini (2008). We examine the influence of role models across generations rather than the link between parents and children. Empirical applications include transmission of work norms from parents to children (Fernandez, Fogli, and Olivetti, 2004; Lindbeck and Nyberg, 2006) and the transmission of religious beliefs (Bisin, Topa, and Verdier, 2004; Bisin and Verdier, 2000).

There is a growing literature on the impact of beliefs or culture on economic outcomes[8] and our paper is closely related to studies of how institutions and policy interact with beliefs. Our question 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). They study the effects of the social system on self reported preferences while we study behavior. Another example is the effect of minimum wage on norms regarding cooperation in the labor market as examined in Aghion, Algan, and Cahuc (2008). We study how exposure to welfare state programs affects demand for social insurance, where demand may be affected by norms with respect to claiming government benefits.[9], [10] Changes in such norms may affect the social capital in society and economic outcomes. Aghion, Algan, Cahuc, and Shleifer

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

[9] Our 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.

[10] A related mechanism is social learning as studied by Fernandez (2008).

(2010) argue that social capital in the form of 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. Our study complements this literature by studying dynamics of norms within one country. Individual panel data allow us a much richer analysis with respect to the intertemporal adaptation and more detailed sets of 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 our intertemporal analysis as discussed above. 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).[11] 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 we 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 to the literature on self reported well-being.[12] What we have labelled 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

[11] 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. Henrekson and Persson (2004) studies sick leave in Sweden in a long time series.

[12] 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 our argument regarding sick leave.

own income and characteristics as well as neighborhood factors.[13, 14] That is, they assume an immediate cross-sectional, usually spatial, effect of the reference group's income/consumption on your well-being. Our model focuses on an intergenerational link the existing empirical literature has not entertained. 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). Our measure of well-being, sick leave, is based on actions, which we think overcome shortcomings of the previous literature.

Our paper is also related to the literature on the intergenerational transmission of economic status, for example father and son earnings correlations as studied in Mulligan (1997) and surveyed in Solon (2002). There are also studies of intergenerational links in welfare take up, Solon, Corcoran, Gordon, and Laren (1988) and Beaulieu, Duclos, Fortin, and Rouleau (2005).[15] That literature focuses on mechanisms within the family, which probably are relevant in our setting as discussed later. However, we allow for broader influences across time and generations that are not limited to family influences.

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.[16] It is very easy to claim the benefits. For the first week of each spell, the law gives the individual

[13] Additional evidence that well-being is partly driven by relative position are Van de Stadt, Kapteyn, and Van de Geer (1985), Clark and Oswald (1996), Blanchflower and Oswald (2004), Ferrer-i-Carbonell (2005), Graham and Felton (2006), Kingdon and Knight (2007), and Clark, Kristensen, and Westergård-Nielsen (2008). Dynan and Ravina (2007) find evidence that relative concerns exist in some domains (like consumption of private goods) but not in others (like leisure and public goods such as defense).

[14] Individual concerns of relative income and consumption and their implications for both taxes and public expenditures have been studied theoretically by Boskin and Sheshinski (1978), Layard (1980), Oswald (1983), Ng (1987), Seidman (1987), Ireland (1998), Ljungqvist and Uhlig (2000), Dupor and Liu (2003), and Abel (2005). Quantifying these relative considerations is an empirical question, where our study makes a contribution.

[15] Oreopoulos, Page, and Stevens (2008) study the effect of parental job loss on children's adult income and program participation.

[16] 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.

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.[17] 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.[18] 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[19]. 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 leaving work 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

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

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

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

first unpaid day is of no consequence, and if it turns out that you're fit for work tomorrow you can change your mind. Spells shorter than 7 days do not pay benefits on weekends. This system was in place until 1987. From 1988 through 1990 the first day of no coverage was abolished.[20, 21]

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

We use registry data on individual panels over the period 1974 to 1990 (from 1973 for lagged income).[22] 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. Our main dependent variable, participation in the sick leave programs, is defined based on observing positive sick leave benefits during the year. We use a random sample of the 1974 population who we follow for 17 years.[23] We include the birth cohorts from 1917 to 1963. About 3 percent of the population is sampled. In addition, household members are included in the data. This allows us to control for the household composition as well as spousal income.

[20] The updates to the program are detailed in law SFS 1987:223.
[21] Reforms in the 1990's make the later data hard to compare to the period we study.
[22] The analysis ends in 1990 since later reforms make the data hard to compare.
[23] The only sampled individuals that disappear from the data are those who die or emigrate.

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 we don't model here, and we choose to exclude those observations. Since the sick leave program is designed to replace lost labor earnings, we restrict the analysis to individuals who are labor force participants.[24] Summary statistics are presented in table 1.

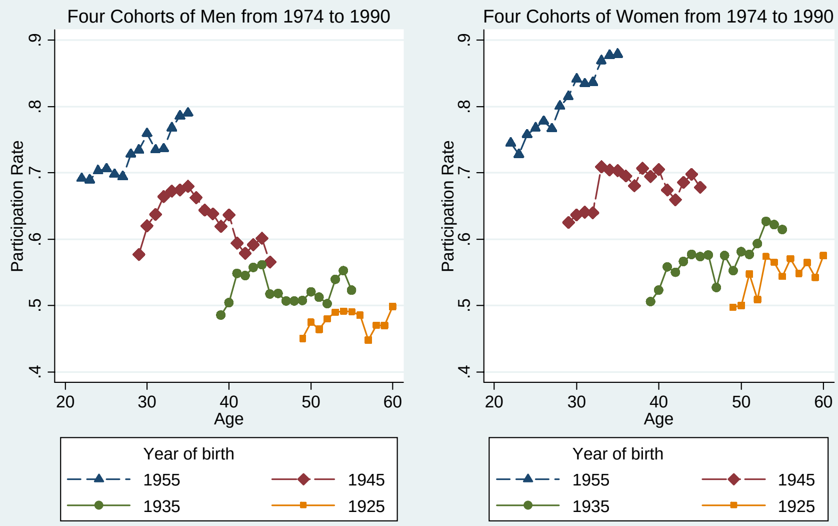
5 Increased Demand For Social Insurance

We account for a number of individual and aggregate factors that could explain the behavioral differences across cohorts seen in figure 1. We also perform a number of robustness checks, yet none of these specifications can account for the pattern in figure 1. We allow for non-linearities in the cohort trend and estimate the model separately for men and women, yet the trend persists.

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

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.[25] In figure 2 we plot the average take up by age for four different cohorts where we can compare cohorts 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.

Figure 2. Sick Leave Participation for Men and Women.



Sample: Labor force participants, ages 22-60.

We may be concerned that changes in labor force participation are behind the increasing sick leave take up across generations. 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.

[25] 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.

So far we have just looked at raw averages. Column 1 of table 2 gives us 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 between estimator, that is, we compare the individual averages over time across individuals. Since the focus is on the differences in behavior across cohorts we think it is the appropriate estimator.

Table 2. Cohort trend in sick leave program participation.

Dependent Variable: Indicator of Positive Sick Leave
Between Estimator

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Year of birth	**0.0080**	**0.0098**	**0.0112**	**0.0110**	**0.0112**	**0.0067**
	(.0001)	(.0003)	(.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	1955700	1930500	1930500	1929100	1929100	1929100

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 in the household.
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 between estimator.
Standard errors in parenthesis. Sample: Labor force participants, 22-60 years old.

One concern may be that the raw average is confounded by life cycle patterns, which may vary by groups as seen in figure 2. We include a full set of interactions between gender, the four education groups,[26] age and age squared. Including these controls raise the estimated cohort trend as seen in column 2. If parents with young children take more sick leave, and these parents are mostly observed among the younger cohorts, it may bias our estimate of the cohort trend upwards. It may hence be important to have detailed controls of the number of children at different ages. Such controls are included in column 3, and the estimated cohort trend increases somewhat.

Younger cohorts tend to have higher education and may have higher earnings (conditional on age) than older cohorts. If sick leave is one dimension of leisure (a normal good), it may be that the higher take up rate is in part an income effect. We 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. We also control for regional business cycles (through the regional employment rate) and regional fixed effects.[27] Including these controls do not affect the cohort trend, as seen in column 4.

It is possible that not only current earnings but lifetime earnings affect the sick leave choice. Using the panel data, we 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 regression is our measure of permanent income, which we include in the regression in column 5. It does not have much of an impact on the cohort trend.

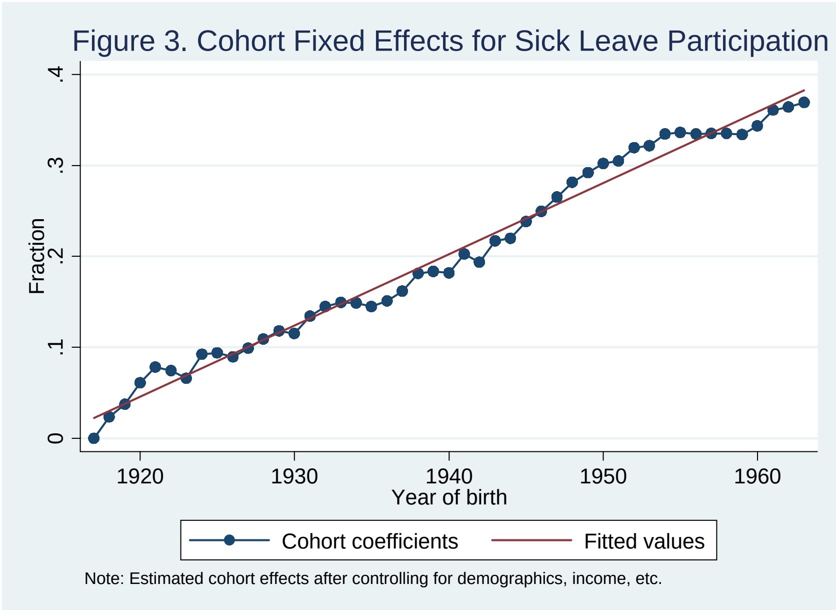
Linearity of the income effects may be a strong assumption that we relax in column 6. We construct five piece splines of both permanent income and lagged income. This allows the income effects to differ across quintiles both for permanent and lagged income. This has a substantial impact on the estimated cohort trend, which now is estimated at 0.67 percentage points. The specification in column 6 will be the baseline in the analysis below.

Linearity of the cohort trend is assumed in table 2. We replace the linear

[26] 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.

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

trend with fixed effects for each cohort. The estimated coefficients are plotted in figure 3.[28] The cohort effects are quite close to a linear trend, so the linearity assumption does not seem to drive the result.



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

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

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.

Even though we controlled for a host of factors 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. These definitional changes could affect the analysis. To examine the impact we redefine the sick leave variable as take up of either of the three programs (sick leave, parental leave, care for sick child). Redefining the dependent variable does not affect the estimated cohort trend.[29]

Since sick leave is not the only program individuals may use it is possible that there is some shifting across programs, which could influence our estimate. To examine the sensitivity to the use of other programs we 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 somewhat lower with this sample restriction, indicating a stronger trend among individuals that use other programs.[30]

The next two alternative specifications deal with the composition of the labor force. Since the main regressions condition on being in the labor force we may be concerned that individuals that have left the labor force would have been on sick leave if the had remained in the labor force. In particular, we may

[29] It's possible that young children are not appropriately controlled for by the linear controls. To address this we 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.

[30] 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. We 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.

be concerned that among the older people only the healthy remain in the labor force, which could drive our finding. To address this we restrict the sample 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 much as seen in specification 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. We redefine sick leave such that all individuals outside the labor force are added to the sick leave rolls (and we no longer condition on being in the labor force). This extreme case provides a lower bound for the cohort trend. The estimated trend is as expected lower, a little shy of half the magnitude, but still significant as shown in column 4. Changes in labor force composition can't explain the cohort trend.

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		Secular drift
Specification	(1)	(2)	(3)	(4)	(5)
Year of Birth	**0.0067**	**0.0048**	**0.0071**	**0.0028**	**0.0048**
	(.0004)	(.0004)	(.0005)	(.0004)	(.0001)
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	1929100	1820100	1292200	2183300	1929100

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

In the fifth specification we examine if the cohort trend could be explained by different take up rates across time by including year fixed effects. In this specification we have to exclude the age controls in order to identify the cohort

[31] Another compositional story would relate to immigrants. We 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.

trend (but we include the gender-education interactions). The estimated cohort trend is still large and significant indicating that the cohort trend can't be explained by generally rising demand for benefits.

We have estimated the model for men and women separately. The cohort trend is a bit stronger for women, and in particular unmarried women. There is no difference between married and unmarried men. 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.

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

Here we interpret higher social insurance take up of younger generations within the structure of a model. 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 economy 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.

Consider a simple model of individual choice similar to Lindbeck, Nyberg, and Weibull (2003), where individuals can choose to claim benefits or not. If

[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.

benefits aren't claimed individuals consume their labor earnings (which may be after tax, with tax revenues not used for the social insurance program used for government consumption that may be valued by individuals but it is separable from private consumption and independent of social insurance take up). If benefits are claimed the worker consumes a fraction ρ of his earnings (ρ represents the replacement 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.[34] ε is a random shock that affects the value of taking up the social insurance benefit for a certain individual in a given year. γ is the utility weight attached to norm adherence. 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. We 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 we obtain the cut off value in the population, 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

[34] In the estimation below we don't impose any parameter restrictions.

m in the previous time period; $\gamma_t = h\left(z_{m,t-1}\right)$.[35] Furthermore, $h : [0,1] \rightarrow \mathbb{R}_+$ and h is continuously differentiable with $h' \leq 0$.

When an individual makes his decision he takes 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 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.

One parametric specification for the psychic cost is

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

where $s_0 > s > 0$. This model can be taken to the data on sick leave take up in Sweden. An individual will take up the benefits if

$$-\ln\rho + \beta - s_0 + s z_{m,t-1} - \varepsilon > 0. \tag{6}$$

We may allow for a number of individual factors to influence the choice. These factors may be captured in 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 $SL^*_{i,n,t}$. We have

$$SL^*_{i,n,t} = \alpha + x_{i,t}\delta + s z_{m,t-1} - \epsilon_{i,t} \tag{7}$$

$$SL_{i,n,t} = \begin{cases} 1 & \text{if } SL^*_{i,n,t} \geq 0 \\ 0 & \text{if } SL^*_{i,n,t} < 0 \end{cases} \tag{8}$$

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

[35] 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.

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.

6.1 Reference groups

Older cohorts, which may include older siblings and classmates, may serve as role models for the individual's current decision. The role models could set a standard for acceptable behavior. Such mechanisms have been discussed in the developmental psychology literature, see for example Harris (1995, 1998). We allow for the psychic cost to be decreasing in the fraction of the reference group that takes up the social insurance benefits.[36]

We assume that the individuals may be influenced by the behavior of older cohorts in a past year. When studying individual sick leave behavior we will relate it to the reference group's average sick leave take up (the z). The reference group (the m) is the cohorts born 2-4 years earlier than the individual in question and who live in the same county.[37] The time lag is 3 years.[38] 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. The time lag captures that the psychic cost may not adjust instantaneously but with a lag.

Our results don't rely on the exact definition of the reference group or the time lag. Results are similar with alternative specifications of the reference group and for alternative time lags as discussed below. We don't interpret our specification to be the one and only social influence on individual behavior. Rather, our specification captures, in an empirically tractable way, the intergenerational spillover that is essential in our model to explain the behavior across

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

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

[38] 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. There are 24 counties in Sweden.

generations in figure 1.[39]

6.2 Results and Interpretations

Our model implies that a shift toward higher take up rates for younger generations should be seen across the sick leave distribution, which is confirmed in the data. The increase of the average take up across generations is illustrated in figure 1. At the extreme ends of the distribution we may consider the share of a cohort that never uses the sick leave program and the share that uses the program every year. Comparing the cohorts born in 1930 and 1950 we find that the share that never takes sick leave has dropped from 12.2 to 1.4 percent, while the share that claims sick leave benefits every year has increased from 10.2 to 20.4 percent. These findings are consistent with the model.

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) we estimate the slope parameter in the psychic cost function (5), 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.[40]

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.[41] Reference group

[39] For example, we 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 mechanims that has not been studied before.

[40] 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.

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

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.

Table 4 presents estimates using both the between and the within estimators.[42] The estimates from the two methods have distinct interpretations, which we explore. The first three specifications use the between estimator, which regress the individual average of the dependent variable on the averages of the independent variables.[43] The estimate on the reference group behavior is identified solely from variation across individuals, which comes from variation across 41 birth cohorts 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. Our estimate is 0.73 as seen in the first specification in table 4. Under the strict assumptions of the model (no omitted variables that affect the estimate) we obtain the slope of the influence of the psychic cost (s in the model). However, if we allow for unobservables, for example initial individual conditions like work norms instilled by parents, that are correlated with average reference group behavior, then the estimate picks up both effects. When we allow for correlation with initial conditions the estimate is a combination of reference group influence (time varying influences) and individual fixed characteristics (culture).

[42] We include the same individual and aggregate controls as in specification 6 in Table 2, except for year of birth.

[43] The estimator is based on time averages within individual, that is, we regress $\overline{SL}_i$ on $\overline{z}_i$ (and other controls).

Table 4. Estimates of lagged stigma in sick leave participation.

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

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

Estimator	Between	Between	Between	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Reference group sick leave behavior in year t-3	**0.728** (.0229)	**0.659** (.0237)	**0.435** (.0246)	**0.182** (.0188)	**0.278** (.0179)
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 between and within estimators. Standard errors in parenthesis. Standard errors of the within estimates adjusted for clustering on birth cohort. Sample: Labor force participants, 22-60 years old. There are 24 counties.

To examine if the between estimate of the reference group influence is only picking up some unobserved characteristic of individuals that differs across generations we estimate the model accounting for unobserved fixed characteristics using the within estimator. Now the estimate is identified from variation in reference group behavior within the same individual.[44] The individual fixed effect captures the slow moving cultural transmission mechanism. 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. We obtain an estimate of 0.18 using the within estimator as seen in specification (4) in table 4, and the estimate is strongly significant.[45]

[44] The estimate is positive if the individual is more likely to take up sick leave in periods when the (lagged) reference group of older people take up relatively more sick leave.

[45] Standard errors for the within estimates are adjusted for clustering on birth cohort.

Under the assumption that average reference group behavior is perfectly correlated with fixed work norms attained as a child (fixed characteristics) the estimate 0.73 in specification (1) provides an upper bound for the combined effect of time varying and fixed influences of the reference group on individual behavior. The within estimate of 0.18 does not include any effect of the fixed characteristics but only the time varying influences.[46] The ratio of the within estimate to the between estimate could be interpreted as a lower bound on the importance of time varying influences compared to cultural transmission.[47] Our estimates indicate that at least one quarter of the total influence of reference group behavior is attributable to time varying influences.[48] For the reasons discussed we don't think this number should be taken literally but it supports the hypothesis that both mechanisms are quantitatively significant.

We find that there is a significant impact of reference group behavior on sick leave take up in our estimation across individuals also after accounting for flexible time effects. In specification (2) we include a linear time trend in the between estimation, which controls for a linear increase in the demand for sick leave over time. The coefficient estimate on reference group behavior drops but it is still strongly significant. We also allow for non linearities in the time effects by including time fixed effects in specification (3).[49] Again, the coefficient estimate on the reference group behavior drops but it is still significant.

The estimated mechanism can account for between three-quarters and nine-tenths of the increasing demand across generations, depending on the specification. The average reference group take up behavior for the cohort born in 1930 is 52.0 percent. For the cohort born in 1950 the corresponding take up

[46] Since it is possible that there are additional social influences not included in our model that affect behavior, which are uncorrelated with our measure of reference group influence, our estimate may be downward biased with respect to all social influences.

[47] By cultural transmission we refer to the influence embodied in the average behavior (across time) of the reference group.

[48] Ichino and Maggio (2000) provides an alternative decomposition of absenteeism in an Italian firm that indicates a lesser role for time varying influences of the reference group but confirms our finding of the importance of fixed individual factors.

[49] The time effects in the between estimation are 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, which may explain the lower estimate in column (3).

is 68.9 percent. Using the between estimate of 0.73 in column (1) we get that the psychic cost increases the younger cohort's take up rate by 12.3 percentage points, which is close to what we estimated in table 2.[50] If we use the estimate in column (3) the effect is a 7.3 percentage points increase for the younger cohort due to the psychic cost.[51]

Returning to the within estimator we may account for time effects also here.[52] Including the year fixed effects alters the interpretation on the estimated coefficient on reference group behavior. 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) indicates a stronger influence of reference group behavior conditional on national behavior.[53, 54]

6.3 Instrumenting for reference group behavior

To further examine our hypothesis we use an instrument to get exogenous shifts in sick leave behavior of the reference group. We use reference group mortality rates to instrument for reference group behavior.[55] The idea is that mortality rates are the result of serious health shocks, which also affect sick leave take up. Implicitly, we only consider variation in reference group behavior that is

[50] 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 13.4 percentage point higher take up rate for the younger cohort.

[51] This number may be most comparable to specification (5) in table 3, which indicates a difference in take up of 9.6 percentage points for cohorts born 20 years apart.

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

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

[54] The estimated within coefficients can't be used to account for the differences in demand across cohorts since all the differences across cohorts are absorbed by the individual fixed effects.

[55] 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.

correlated with these serious health shocks.[56]

We observe mortality rates per 1000 population by year, age and county. We assume that mortality follows a simple model with a second order polynomial in age and a random shock. If we denote the mortality rate in county c, for the generation born in year g, in year t by $MR_{c,g,t}$ we have

$$MR_{c,g,t} = \alpha_0 + \alpha_1 Age_t + \alpha_2 Age_t^2 + \varepsilon_{c,g,t} \tag{9}$$

We assume that the mortality shocks are i.i.d. across counties, generations, and years. The model explains about 85 percent of the variation in the data. As our 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. We could also allow more complex models of mortality, for example with year fixed effects[57] but it would not affect our analysis in the specifications that control for year fixed effects.

The mortality rates we use as instruments are defined in the same way the reference group behavior is defined. 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, lagged 3 years. 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]

We estimate our models 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. The instrument is not weak.[59]

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

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

[58] More formally, the assumption is that the mortality shocks in (9) 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 (7).

[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.

Table 5. Instrumental variables estimates of lagged stigma.

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

Estimator	Between	Between	Between	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Reference group sick leave behavior in year t-3	**0.674**	**0.876**	**0.627**	**0.785**	**1.038**
	(.0898)	(.0695)	(.0793)	(.135)	(.1457)
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 between and within estimators.
Standard errors in parenthesis. Standard errors of the within estimates adjusted for clustering on birth cohort.
Sample: Labor force participants, 22-60 years old. There are 24 counties.

The results are presented in table 5. The first estimate from the between estimator is 0.67. Including a year trend produces an estimate of 0.87, larger than without the instrument. The between estimate with fully flexible year effects is 0.63, again a bit larger than the OLS estimate.

Instrumenting has a big impact on the within estimates, which are now much larger in magnitude. The estimate is 0.78 in column four.[60] Adding the year fixed effects increases the estimate as it did in table 4. 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

[60] 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.

through the year effect.

Overall, the estimated influence of role model behavior is larger when we instrument using mortality rates. Role model behavior shifted by these health shocks has a substantial influence on individual behavior. 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. The range 0.75 to 0.78 are within the 95 percent confidence intervals of all the estimates. That the between and within estimates aren't substantially different would indicate the there aren't omitted variables correlated with sick leave behavior that drive the result as the omitted factors controlled for in the individual fixed effect doesn't affect the estimates much.

The coefficients in table 5 can't be used to assess the relative importance of fixed versus time varying influences as we did in table 4. The purpose of using the instrument is to isolate the influence of role model behavior through the channel of exogenous health shocks. By doing so we avoid the potential influence of culture (fixed influences) discussed above.

Challenges to our 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 effect we set out to estimate. However, we control for average labor earnings by county to capture such trends.[61]

Furthermore, our results are robust to including the current mortality rate of the individual's own cohort as a control variable, as seen in table 6.[62,63,64] Omitted

[61] Our results are also robust to controlling for county level fixed effects.

[62] The results are also robust to controlling for the own cohort's mortality rate lagged 3 years (rather than the current rate).

[63] This may be interpreted as relaxing the assumption that the health shocks in (9) are independent across generations and time.

[64] The relatively weak influence of the own cohorts mortality rate in table 6 may seem at

trends that would challenge our 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.

Table 6. Instrumental variables estimates while controlling 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: Cohorts born 2-4 years earlier, living in individual's county
Time lag: 3 years

Estimator	Between	Between	Between	Within	Within
Specification	(1)	(2)	(3)	(4)	(5)
Reference group sick leave behavior in year t-3	**0.668**	**0.823**	**0.476**	**0.758**	**1.019**
	(.1227)	(.0999)	(.1183)	(.1381)	(.1521)
Own cohort's mortality rate in year t	**0.0002**	**0.0028**	**0.0072**	**0.0014**	**0.0008**
	(.0028)	(.0031)	(.0032)	(.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 between and within estimators.
Standard errors in parenthesis. Standard errors of the within estimates adjusted for clustering on birth cohort.
Sample: Labor force participants, 22-60 years old. There are 24 counties.

We argue that our approach deals with potential sorting, for example that individuals with a high valuation of leisure could move to places where the psy-

odds with the first stage results. However, we 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 our results indicate that this noise is cancelled out when averaged across cohorts.

chic 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 we use unexplained mortality shocks 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.

Our results don't rely on the particular reference group or the time lag. We find similar results when the time lag is 1 year or 5 years. The results are also similar if we 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).[65] As a falsification test we have also estimated a model where we 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 our hypothesis. The estimated effect is insignificant at conventional levels, in line with our hypothesis.

We 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. We may entertain stories that there are local trends in for example drug abuse that affect both sick leave and mortality. Such trends could potentially challenge our 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.[66] Using reference group mortality as an instrumental variable, and

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

[66] 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

controlling for the mortality of the individual's own cohort, makes a compelling case that we have identified one channel of intertemporal influence in sick leave choices.

7 Conclusion

How do individuals adapt to institutions? Plenty of evidence show that institutions shape different outcomes across locations.[67] However, precious little evidence exists on how these outcomes come about. Basically, we know that societies and communities end up with different outcomes based on the institutions they face or faced, but we know very little about how they got there.

We study the adaptation in demand for social insurance over time and across generations in Sweden following an expansion of the social insurance programs. Our evidence shows how individuals adapt to the expanded welfare state. We document substantial differences in behavior, almost one percentage point higher program up take per birth cohort, although program rules have been constant for decades.

We model a preference mechanism and evaluate to what extent it can explain the rapid increase in benefits take up across cohorts. We allow individuals' benefit take up decision to depend on the behavior of 'role models.'[68] We find a significant influence of role model behavior on individual benefit take up, which can account for a majority of observed behavioral differences across cohorts. This is the first paper to estimate the dynamic adaptation of norms to behavior in the welfare state, as little empirical evidence exists regarding what forces shape norms. The underlying mechanism we study is present in several literatures[69] yet few papers *empirically* evaluate how economic outcomes affect preferences and norms.

variation we use to identify our estimate.

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

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

[69] 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.

We provide evidence on how norms evolve and how they affect behavior using a large individual panel data set. We exploit variation across different generations as well as variation across time within individuals to estimate a model where the take up decisions depend on the past behavior of role models. We find that being exposed to older generations that used the sick leave program more is associated with higher individual demand for the program. We use reference group mortality rates to instrument for reference group behavior to address concerns that omitted variables, such as local health or productivity trends, may drive our results. We find that movements in reference group behavior due to mortality shocks have a substantial impact on individual decisions to take up sick leave. The IV/2SLS results point to a strong and robust intertemporal influence of reference group behavior on individual decisions.

We 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 we model, but our mechanism and our results are quite general. Our intertemporal mechanism does not preclude that for example spatial interactions are present or that there are additional intertemporal mechanisms. We find that our model captures a quantitatively significant mechanism, and with our instrumented results we provide compelling evidence that the intertemporal mechanism is indeed one channel of influence on individual decisions.

The intertemporal adaptation mechanism we estimate may apply to all kinds of welfare state programs. Our 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.[70] This is a consistent finding across

[70] 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.'

countries, including Sweden, and indicates that the intertemporal mechanism at work in Sweden could be relevant elsewhere.[71] Our model could apply to other social insurance programs and to programs with different levels of generosity as the intertemporal mechanism does not depend on program 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. We 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. Our analysis indicates that large policy reforms don't take place in a static environment. 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 our unique contributions to the literature.

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