Sick of the Welfare State? Sticky Stigma and Demand for Social Insurance

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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, I38, J22

Key words: social insurance, norm dynamics, role models

1 Introduction

We observe that young generations demand substantially more social insurance benefits than older generations, although program rules have been constant for decades. Our hypothesis is that older generations who grew up before the advent of the welfare state and with less experience of other people claiming its social insurance benefits have a large stigma against claiming government benefits. Younger generations who experience more people using social insurance programs have smaller stigma. We develop and estimate a model where past take up rates of older generations affect current decisions.

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Our model builds on theoretical studies of long term welfare state dynamics by Lindbeck, Nyberg, and Weibull (1999, 2003).[1] Empirical evaluations of such models are scarce. Our contributions are, first, to quantify the long term increases in demand for social insurance; second, to estimate a mechanism that can account for the intertemporal behavior; and third, to apply a new empirical strategy to identify the mechanism.

This paper makes novel contributions to several existing literatures.[2] We contribute to the social interactions literature where we focus on intertemporal spillovers rather than spatial. We add to the emerging field of culture and economics by a careful study of how the supply of welfare state programs affects individual behavior. Our outcome variable, sick leave, is a measure of well-being. We provide an intertemporal link in the study of well-being the existing literature does not consider. While the literatures on culture and well-being have relied on self reported surveys we analyze actions.

We are able to isolate the demand for social insurance benefits by studying a program where the decision to take up benefits is entirely demand determined. We 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. The stigma we model, which operates on the demand for benefits, would apply to any social insurance program. We choose to study this particular program because behavior reveals demand without supply interference.

The take up of sick leave benefits has been increasing over time, from 54 percent in 1974 to 69 percent in 1990.[3] This increased take up is not uniform across the population. There is a pronounced increase in take up rates across generations, with young generations having 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

[1] Lindbeck (1995) discusses several mechanisms that may result in delayed responses to welfare state policies.

[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.

the take up rate is almost 80 percent.[4]

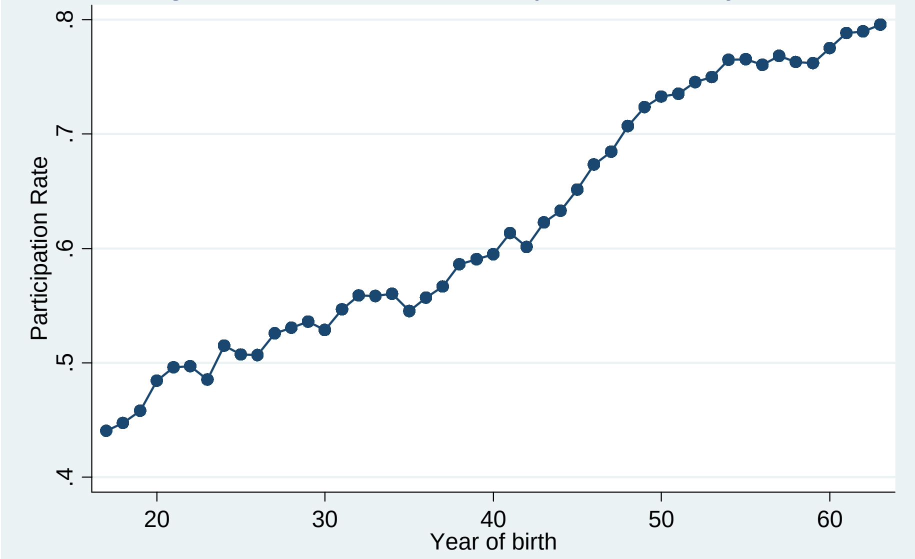


Figure 1. Sick Leave Participation Rate by Cohort

Sample: Labor force participants, ages 22-60. Years 1974-1990.

The raw averages suggest that each younger birth cohort has a take up rate that is almost 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.

The steady increase in take up rates for younger generations is consistent with an economic model of stigma. We write down an empirical model of stigma, based on Lindbeck, Nyberg, and Weibull (2003). We estimate a stigma function and quantify how older cohorts' past behavior influences individual behavior.[5] The estimated model can account for three-quarters of the increased demand across generations.

We estimate the importance of stigma versus a general shift over time to-

[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.

[5] A model of spatial stigma can't explain the pattern in figure 1 as cohorts are quite evenly distributed across locations.

wards 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 stigma that varies over time. This provides a quantification of the relative importance of social interactions compared to culture. Culture is considered the slow moving part of preferences,[6] for example the work norms instilled by your parents, while social interactions are fast moving influences on preferences, for example the influence of your current colleagues' on your work norms.

We apply an instrumental variables approach to identify the intertemporal influence of social interactions. 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.

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 of stigma and we present the empirical results. Section 7 concludes.

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 stigma, 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 has been modeled by Bisin and Verdier (2001), Lindbeck and Ny-

[6] This distinction between social interactions and culture is discussed in Guiso, Sapienza, and Zingales (2006).

berg (2006), Tabellini (2008), and Doepke and Zilibotti (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; Guiso, Sapienza, and Zingales, 2003).

Social interactions in social insurance benefits have been studied empirically. 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 by Bertrand, Luttmer, and Mullainathan (2000) and Edin, Fredriksson, and Åslund (2003).[7] The effects of social norms have been studied in the context of unemployment insurance, a related social insurance program, see Stutzer and Lalive (2004) and Clark (2003). None of these studies of social interactions have analyzed behavioral effects across generations, which we do.

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

[7] Two recent 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.

[8] See for example Guiso, Sapienza, and Zingales (2006, 2008, 2009).

[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).

capital in society and economic outcomes. Aghion, Algan, Cahuc, and Shleifer (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 more detailed sets of controls, including fixed individual characteristics, where the related literature to a large extent rely on country level variation.

The mechanism in our paper is analytically similar to external habits that have been used to explain asset prices in for example Abel (1990) and Campbell and Cochrane (1999). The norms in our model introduce an externality, which may have implications for policy. 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.

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.[11] What we have labelled stigma 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.[12] That is, they as-

[11] See for example Easterlin (1974, 1995, 2001).

[12] 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).

sume 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).[13] 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.[14] 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.[15] 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

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

[14] 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.

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

your condition. 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 shocks. 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[16]. 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 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.[17]

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

[16] The updates to the program are detailed in law SFS 1973:465.
[17] The updates to the program are detailed in law SFS 1987:223.

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). 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.[18] 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.

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.

[18] The only sampled individuals that disappear from the data are those who die or emigrate.

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.[19] Summary statistics are presented in table 1.

5 Increased Demand For Social Insurance

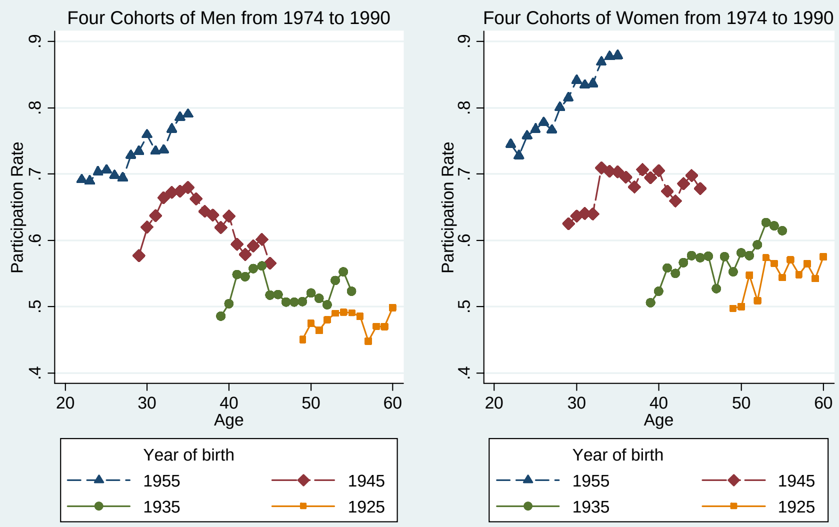
We account for a number of individual and aggregate factors that could explain the behavioral differences across cohorts seen in figure 1. We also perform a number of robustness checks, yet none of these specifications can account for the pattern in figure 1. We allow for non-linearities in the cohort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

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] 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.

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

[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.

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[21] 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.

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 between individuals. Since the focus is on the differences in behavior across cohorts we think it is the appropriate estimator.

[21] Labor force participation is defined as having positive income from work during the year.

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,[22] 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

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

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.[23] Including these controls do not affect the cohort trend, as seen in column 4.

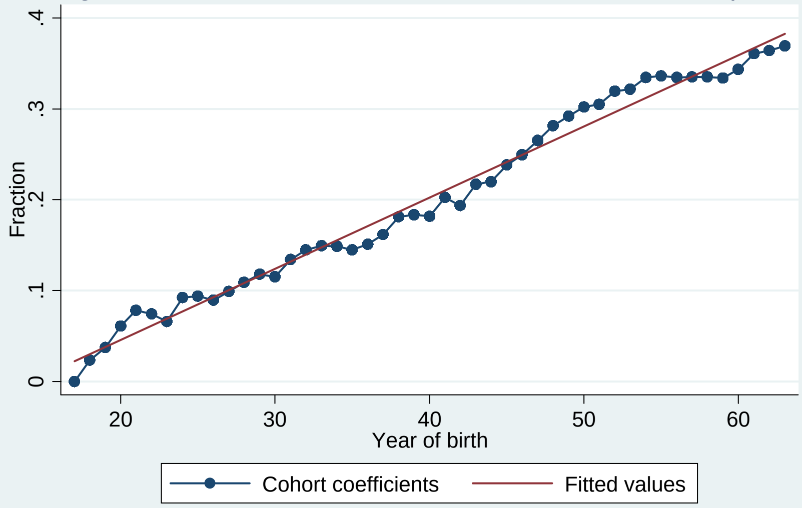
It is possible that not only current earnings but lifetime earnings affect the sick leave choice. Using the panel data, we run an individual fixed effect (within) regression of individual earnings on the age-gender-education interactions mentioned above and business cycle controls. The individual fixed 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 trend with fixed effects for each cohort. The estimated coefficients are plotted in figure 3.[24]The cohort effects are quite close to a linear trend, so the linearity assumption does not seem to drive the result.

[23]Our objective is not to explain regional differences in take up.
[24]Being born in 1917 is the omitted category.

Figure 3. Cohort Fixed Effects for Sick Leave Participation



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

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 have 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.

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.[25]

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 is somewhat lower with this sample restriction, indicating a stronger trend among individuals that use other programs.[26]

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 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

[25] 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.

[26] 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.

in specification 3.[27] 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.

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 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.

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.

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

[27] 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.

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.[28] 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.

6 A Mechanism: Sticky Stigma

Here we interpret higher social insurance take up of younger generations within the structure of a model of stigma. The stigma 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), stigma 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 stigma. With stigma 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 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 stigma γ. The

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

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. 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

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

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

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

The current stigma depends on the share of transfer recipients in group m in the previous time period; $\gamma_t = h\left(z_{m,t-1}\right)$. Furthermore, $h : [0, 1] \to \mathbb{R}_+$ 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 stigma, 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 stigma 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 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 stigma to be decreasing in the fraction of the reference group that takes up the social insurance benefits.[29]

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. The time lag is 3 years.[30] The adjustment of stigma 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 stigma may not adjust instantaneously but with a lag.[31]

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

[29] 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.'

[30] 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.

[31] Our results don't rely on the exact definition of the reference group or the time lag. It does however capture the intergenerational spillover that is essential in our model to explain the behavior across generations in figure 1.

(conditional on the control variables) we estimate the slope parameter in the stigma 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 stigma, which induce other individuals to take up the benefits, and so on.[32]

If the real world is more complex than the model then the interpretation of the estimates may change. It is possible that the true stigma is unobserved, that is, the stigma is an omitted variable like attitudes and beliefs of the reference group that in turn affect individual behavior.[33] 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 stigma 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.[34] 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.[35] 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

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

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

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

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

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 stigma (s in the model). However, if we allow for unobservables, for example initial individual conditions like work norm 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 (social interactions) and individual fixed characteristics (culture).

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

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

Refrerence 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**	**0.659**	**0.435**	**0.182**	**0.278**
	(.0229)	(.0237)	(.0246)	(.0188)	(.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.[36] The individual fixed effect captures the slow moving cultural transmission mechanism. A significant estimate of reference group behavior would support the presence of social interactions, that there is an influence of stigma 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.[37]

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 stigma and cultural transmission on individual behavior. The within estimate of 0.18 does not include any effect of the fixed characteristics but only the stigma.[38] The ratio of the within estimate to the between estimate could be interpreted as a lower bound on the importance of social interactions compared to cultural transmission. Our estimates indicate that at least one quarter of the total influence of social interactions and cultural transmission is attributable to social interactions.[39] 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). Again, the coefficient

[36]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.

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

[38]Since it is possible that there are additional social interactions not include in our model that influence behavior, which are uncorrelated with our measure of lagged stigma, our estimate may be downward biased with respect to all social interactions.

[39]By social interactions we refer to the impact of lagged stigma. Cultural transmission refers to individual fixed characteristics like work norms instilled by parents.

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 is 68.9 percent. Using the between estimate of 0.73 in column (1) we get that stigma increases the younger cohort's take up rate by 12.3 percentage points, which is close to what we estimated in table 2.[40] If we use the estimate in column (3) the effect is a 7.3 percentage points increase for the younger cohort due to stigma.[41]

Returning to the within estimator we may account for time effects also here.[42] 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.[43, 44]

6.3 Instrumenting for reference group behavior

To further examine our hypothesis we use reference group mortality rates to instrument for reference group behavior. The idea is that mortality rates are the result of serious health shocks, which also affect sick leave take up. Implicitly,

[40] The raw average in column (1) indicates a 16 percentage point higher take up rate for the cohort born 20 years later. The estimate in column (6) of table 1 produces a 13.4 percentage point higher take up rate for the younger cohort.

[41] 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.

[42] 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.

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

[44] 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.

we only consider variation in reference group behavior that is correlated with these serious health shocks.[45]

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[46]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.[47]

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.[48]

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

[46] 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.

[47] 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).

[48] The instrument has t-values of at least 5 in first stage regressions, and tests based on

Table 5. Instrumental variable 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

Refrerence 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. Adding the year fixed effects increases the estimate as it did in table 4. The estimated coefficient is now 1.04, indicating a very strong influence of reference group behavior when we condition on the national average behavior 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

Kleibergen-Paap statistics reject the hypotheses of weak instruments and underidentification.

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 culture versus social interactions 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 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.

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.[49,50,51] Omitted trends that would challenge our identification would not only have to correlate with the reference group's mortality across counties, cohorts, and time; the

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

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

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

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

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

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

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

Estimator Specification	Between (1)	Between (2)	Between (3)	Within (4)	Within (5)
Reference group sick leave behavior in year t-3	**0.668** (.1227)	**0.823** (.0999)	**0.476** (.1183)	**0.758** (.1381)	**1.019** (.1521)
Own cohort's mortality rate in year t	**0.0002** (.0028)	**0.0028** (.0031)	**0.0072** (.0032)	**0.0014** (.0007)	**0.0008** (.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 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.[52] Using reference group mortality as an instrumental variable, and 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

Norms against living off the government, while once strong, may be eroding as more people use welfare state programs. We assess the speed at which this erosion of social norms affects observed behavior. 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.

We estimate a substantial increase in the take up of benefits across generations, a little short of 1 percentage point per birth cohort. This quantifies the speed at which behavior changes but it does not provide a mechanism behind the increased demand for the benefits. To explain the cohort trend we model a preference mechanism; stigma. We allow individuals' benefit take up decision to depend on the behavior of 'role models.' Preferences are modeled such that the threshold for claiming benefits depends on your experience with role model behavior. We find a significant influence of role model behavior on individual benefit take up, which can account for a large fraction of observed behavioral differences across cohorts.

The underlying mechanism we study is present in several literatures. The program participation literature talks about stigma affecting choices. The lit-

[52] 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 we use to identify our estimate.

erature on culture asks how beliefs affect economic outcomes. Yet few papers evaluate how economic outcomes affect preferences and norms.

Understanding how norms[53]evolve is important in all of these literatures. However, little empirical evidence exists regarding what forces shape norms. We provide evidence on the dynamics of norms and how they affect behavior using a large individual panel data set.

We write down and estimate a model where individual take up decisions may depend on the behavior of older generations in the past. Being exposed to older generations that used the program more is associated with higher individual demand for the program. The relationship is found using both variation across different generations and variation across time within individuals.

To further examine our hypothesis of social interactions we use reference group mortality rates to instrument for reference group behavior. We find that movements in reference group behavior due to mortality rates have a substantial impact on individual decisions to take up sick leave. The IV/2SLS results point to a strong influence of intertemporal social interactions.

Our finding 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 tend to have a higher acceptance of claiming public benefits one is not entitled to according to the World Values Survey.[54]This is a consistent finding across countries, including Sweden. This pattern is robust to controlling for gender, education, employment status, marital status, income, country fixed effects, and survey wave effects. This evidence on attitudes across a broad set of countries is consistent with the behavior across generations in Sweden. It indicates that the behavioral pattern found in Sweden could be relevant elsewhere.

We have learned that fixed individual characteristics are quantitatively important factors behind the demand for social insurance benefits, yet we have not

[53]By norms we mean to capture the concepts of stigma, culture, beliefs, habits, and positional concerns used in the literatures mentioned above.

[54]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'.

explained how these fixed characteristics are formed. We'd like to learn what the individual fixed effect picks up, for example to what extent parental influences may account for individuals' fixed initial conditions such as work norms. Preliminary results from a related study indicate significant associations between parental labor supply during the child's formative years and the benefit up take when the child has reached his 20's. This evidence is consistent with intergenerational transmission of work norms.

Our intertemporal mechanism does not preclude that for example spatial interactions are present or that there are additional intertemporal mechanisms. Our model would 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. 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.

References

[1] Abel, Andrew B., "Asset Prices under Habit Formation and Catching Up with the Joneses," American Economic Review, LXXX (1990), 38–42.

[2] Abel, Andrew B., "Optimal Taxation When Consumers Have Endogenous Benchmark Levels of Consumption," Review of Economic Studies, LXXII (2005), 1–19.

[3] Aghion, Philippe, Yann Algan, and Pierre Cahuc (2008). "Can Policy Interact with Culture? Minimum Wage and the Quality of Labor Relations." Working paper.

[4] Aghion, Philippe, Yann Algan, Pierre Cahuc, and Andrei Shleifer (2010). "Regulation and Distrust ." Quarterly Journal of Economics 125:3.

[5] Alesina, Alberto and Nicola Fuchs-Schündeln (2007). "Goodbye to Lenin (or not?): The effect of Communism on people's preferences." American Economic Review, Volume: 97, Issue: 4, 1507-1528.

[6] Algan, Yann, and Pierre Cahuc (2010). "Inherited Trust and Growth." Forthcoming, the American Economic Review.

[7] Beaman, Lori, Raghabendra Chattopadhyay, Esther Duflo, Rohini Pande, Petia Topalova (2009). "Powerful Women: Does Exposure Reduce Bias?" Quarterly Journal of Economics, 124:4, 1497-1540.

[8] Beaulieu, N., J.-Y. Duclos, B. Fortin, and M. Rouleau (2005). "Intergenerational reliance on social assistance: Evidence from Canada." Journal of Population Economics 18 (3), 539-562.

[9] Bertrand, Marianne, Erzo Luttmer, and Sendhil Mullainathan (2000). "Network Effects and Welfare Cultures." Quarterly Journal of Economics, August, pp. 1019-1055.

[10] Bertrand, Marianne, and Sendhil Mullainathan (2001). "Do People Mean What They Say? Implications for Subjective Survey Data." The American Economic Review, Vol. 91, No. 2, pp. 67-72.

[11] Bisin, Alberto, Giorgio Topa, and Thierry Verdier (2004). "Religious Intermarriage and Socialization in the United States." Journal of Political Economy, vol. 112, no. 3, .615-64

[12] Bisin, Alberto and Thierry Verdier (2001). "The Economics of Cultural Transmission and the Dynamics of Preferences." Journal of Economic Theory 97, 298-319.

[13] Bisin, Alberto and Thierry Verdier (2000). "Beyond the melting pot: cultural transmission, marriage, and the evolution of ethnic and religious traits." The Quarterly Journal of Economics, August, 955-988.

[14] Blanchflower, David G., and Andrew J. Oswald, “Well-Being over Time in Britain and the USA,” Journal of Public Economics, LXXXVIII (2004), 1359–1386.

[15] Boskin, Michael, and Eytan Sheshinski, “Optimal Redistributive Taxation When Individual Welfare Depends on Relative Income,” Quarterly Journal of Economics, XCII (1978), 589–601.

[16] Campbell, John Y., and John H. Cochrane, “By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior,” Journal of Political Economy, CVII (1999), 205–251.

[17] Clark, Andrew E. (2003). "Unemployment as a social norm: psychological evidence from panel data." Journal of Labor Economics, 2003, vol. 21, no.2, 323-351.

[18] Clark, Andrew E., Nicolai Kristensen, Niels Westergård-Nielsen (2009). "Economic Satisfaction And Income Rank In Small Neighbourhoods." Journal of the European Economic Association, 7(2–3):519–527.

[19] Clark, Andrew E., and Andrew J. Oswald, “Satisfaction and Comparison Income,” Journal of Public Economics, LXI (1996), 359–381.

[20] Doepke, Matthias and Fabrizio Zilibotti (2008). "Occupational choice and the spirit of capitalism." The Quarterly Journal of Economics, May, 747-93.

[21] Dupor, Bill, and Wen-Fang Liu, “Jealousy and Equilibrium Overconsumption,” American Economic Review, XCIII (2003), 423–428.

[22] Dynan, Karen E. and Enrichetta Ravina . “Increasing Income Inequality, External Habits, and Self-Reported Happiness.” The American Economic Review, P & P, vol. 97 no. 2 (2007), 226-31.

[23] Easterlin, Richard A., “Does Economic Growth Improve the Human Lot? Some Empirical Evidence,” in Nations and Households in Economic

Growth: Essays in Honor of Moses Abramowitz, Paul A. David and Melvin W. Reder, eds. (New York, NY: Academic Press, 1974).

[24] ——, “Will Raising the Incomes of All Increase the Happiness of All?” Journal of Economic Behavior and Organization, XXVII (1995), 35–48.

[25] ——, “Income and Happiness: Towards a Unified Theory,” Economic Journal, CXI (2001), 465–484.

[26] Edin, P-A, P Fredriksson, and O Åslund (2003). “Ethnic enclaves and the economic success of immigrants - evidence from a natural experiment." Quarterly Journal of Economics, Vol. 118, No. 1, pp. 329-357.

[27] Fernandez, Raquel (2008). "Culture as Learning: The Evolution of Female Labor Force Participation over a Century." Mimeo, New York University.

[28] Fernandez, Raquel, Alessandra Fogli, and Claudia Olivetti (2004). "Mothers and sons: Preference formation and female labor force dynamics." The Quarterly Journal of Economics, November, 1249-99.

[29] Ferrer-i-Carbonell, Ada, “Income and Well-Being: An Empirical Analysis of the Comparison Income Effect,” Journal of Public Economics, LXXXIX (2005), 997–1019.

[30] Graham, Carol, and Andrew Felton (2006). “Inequality and Happiness: Insights from Latin America.” Journal of Economic Inequality, 4, 107–122.

[31] Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2003). "People’s opium? Religion and Economic Attitudes." Journal of Monetary Economics, 50:1, pp. 225-82.

[32] Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2006). "Does culture affect economic outcomes?" Journal of Economic Perspectives, volume 20, no 2, 23-48.

[33] Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2008). "Social Capital as Good Culture." Journal of European Economic Association, 6(04-05): 295-320.

[34] Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2009). "Cultural Biases in Economic Exchange?" Quarterly Journal of Economics. 124(4), 1095–1131.

[35] Harris, Judith Rich (1995). "Where is the child's environment? A group socialization theory of development." Psychological Review, Vol 102, No. 3, 458-489.

[36] Harris, Judith Rich (1998). "The nurture assumption: why children turn out the way they do." New York: Free Press.

[37] Henrekson, M. and M. Persson (2004). "The Effects on Sick Leave of Changes in the Sickness Insurance System." Journal of Labor Economics 22 (1), 87-113.

[38] Hesselius P, P Johansson & P Nilsson, "Sick of Your Colleagues' Absence?", Journal of the European Economic Association, April 2009, Vol. 7, No. 2-3, Pages 583-594.

[39] Ireland, Norman J., "Status-Seeking, Income Taxation and Efficiency," Journal of Public Economics, LXX (1998), 99–113.

[40] Kingdon, Geeta, and John Knight (2007). "Community, Comparisons and Subjective Well-Being in a Divided Society." Journal of Economic Behaviour & Organization, 64, 69–90.

[41] Layard, Richard, "Human Satisfactions and Public Policy," Economic Journal, XC (1980), 737–750.

[42] Lindbeck, Assar (1995). "Hazardous Welfare-State Dynamics." American Economic Review, May, vol. 85, no. 2.

[43] Lindbeck, Assar and Sten Nyberg (2006). ”Raising Children to Work Hard: Altruism, Work Norms and Social Insurance.” Quarterly Journal of Economics, November, 1473-1503.

[44] Lindbeck, Assar, Sten Nyberg, and Jörgen Weibull (1999). "Social Norms and Economic Incentives in the Welfare State". Quarterly Journal of Economics, vol. 114, no. 1, 1-35.

[45] Lindbeck, Assar, Sten Nyberg, and Jörgen Weibull (2003). "Social Norms and Welfare State Dynamics". Journal of the European Economic Association, April–May 1(2–3):533–542.

[46] Lindbeck, Assar, Mårten Palme, and Mats Persson (2008). "Social Interactions and Sick Leave." Mimeo, Stockholm University.

[47] Ljungqvist, Lars, and Harald Uhlig, “Tax Policy and Aggregate Demand Management under Catching Up with the Joneses,” American Economic Review, XC (2000), 356–366.

[48] Luttmer, Erzo F. 2005. "Neighbors as Negatives: Relative Earnings and Well-Being." Quarterly Journal of Economics. 120:3, pp. 963-1002.

[49] Manski, Charles F. (1993). "Identification of endogenous social effects: The reflection problem." Review of Economic Studies, 60(3): 531-42.

[50] Moffit, R. (1983): An Economic Model of the Welfare Stigma. American Economic Review 73(5): 1023-35.

[51] Mulligan, Casey B. (1997). "Parental priorities and economic inequality." The University of Chicago Press.

[52] Ng, Yew-Kwang, “Relative-Income Effects and the Appropriate Level of Public Expenditure,” Oxford Economic Papers, XXXIX (1987), 293–300.

[53] Oreopoulos, Philip, Marianne Page, and Ann Huff Stevens, 2008. "The Intergenerational Effects of Worker Displacement." Journal of Labor Economics, vol. 26, no. 3, pp. 455-483.

[54] Oswald, Andrew J., “Altruism, Jealousy and the Theory of Optimal Non-Linear Taxation,” Journal of Public Economics, XX (1983), 77–87.

[55] Ravallion, Martin, and Michael Lokshin, “Identifying Welfare Effects from Subjective Questions,” Economica, LXVIII (2001), 335–357.

[56] Seidman, Laurence S., “Relativity and Efficient Taxation,” Southern Economic Journal, LIV (1987), 463–474.

[57] Skogman Thoursie, Peter, 2004. "Reporting Sick: Are Sporting Events Contagious?" Journal of Applied Econometrics, vol. 19, no. 6, 809-823.

[58] Solon, Gary (2002). "Cross-Country Differences in Intergenerational Earnings Mobility." The Journal of Economic Perspectives, Vol. 16, No. 3, pp. 59-66.

[59] Solon, Gary, Mary Corcoran, Roger Gordon, and Deborah Laren. "Sibling and Intergenerational Correlations in Welfare Program Participation." The Journal of Human Resources, Vol. 23, No. 3 (Summer, 1988), pp. 388-396.

[60] Stutzer, Alois and Rafael Lalive (2004). "The role of social work norms in job searching and subjective well-being." Journal of the European Economic Association, 2 (4), 696-719.

[61] Tabellini, Guido (2008). "The scope of cooperation: values and incentives." The Quarterly Journal of Economics, August, pages 905-950.

[62] Van de Stadt, Huib, Arie Kapteyn, and Sara van de Geer, “The Relativity of Utility: Evidence from Panel Data,” Review of Economics and Statistics, LXVII (1985), 179–187.