The market for creampuffs:

Big Data and the transformation of the welfare state

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Abstract: The literature on the welfare state assumes, often implicitly but almost universally, that social insurance can or will be provided through the state. This assumption is based on economic models of insurance that show the propensity for market failure when information is limited and privately held. With the data revolution this is no longer a satisfactory approach, and this paper asks what happens when information rises and can be credibly shared with insures. Our model shows that Big Data alters the politics of social insurance by increasing polarization over the level and cost-sharing of public provision, and sometimes by creating majorities for a shift towards segmented and inegalitarian private markets (a shift that is conditioned by government partisanship). Preliminary evidence is consistent with key predictions of our model.

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Introduction

A central function of the welfare state is to provide social insurance. Indeed, a voluminous literature underscores that political support for social spending in the pivotal middle and upper-middle classes rests on their demand for insurance against risks like unemployment, illness, and old age (e.g., Baldwin 1990; Esping-Andersen 1990; Iversen and Soskice 2001; Moene and Wallerstein 2001). Underlying most of these analyses is an assumption, often implicit but virtually universal, that social insurance cannot be provided effectively through the market due to incomplete and asymmetric information (Barr 2012; Boadway and Keen 2000). While this assumption may have been approximated in the past, the data revolution is making it untenable. This paper asks what happens to the welfare state when information about health, unemployment risks, life expectancy, credit-worthiness, and so on, becomes more widely available and shareable. Theory and evidence suggest that this will have major consequences for the politics of social protection.

A hint of what is to come can be gleaned from the car insurance market, where information technology is radically transforming the status quo. There are now more than a dozen insurance companies in the US offering "pay as/how you drive" policies which tie premiums to driving behavior (based on a black box that tracks distance, acceleration, braking, cornering forces, speeds relative to speed limits, among other things). Unsurprisingly, safe drivers flock to these plans. Something similar may be happening in life- and health insurance. For example, John Hancock Life Insurance, a major player in the American market, introduced a policy that calculates annual premiums partially based on data collected by an "activity tracker" that policy-holders receive for free when they sign up. These types of devices (which include smartphones equipped with the right app) can track and instantly share things like: steps and stairs taken, active minutes, calories burned, heart rate, sleep quality, blood pressure, among others. The company markets this life insurance policy as "an innovative solution that rewards you for living a healthy life. In fact, the healthier you are, the more you can save." All the leading technology companies – Apple, Alphabet, Microsoft, etc. – are committing huge resources to developing a new data-based health industry; yet there is currently no analytical framework within which to understand the consequences of Big Data for politics and inequality. This paper proposes such a framework.

Our main thesis can be summarized in two key propositions: First, the data revolution expands the range of social protection that can be provided privately, which undermines cross-class support for the welfare state and makes more likely either an expansion of private markets, or the introduction of market mechanisms in public provision. Left governments that represent more risk-exposed individuals may slow this change, but the growing feasibility of market solutions puts pressure on politicians of all stripes to permit markets to work. Second, even when social protection continues to be provided through the state, political support will polarize as information about risks becomes more ubiquitous. We are only in the beginning of this process, but we believe it is critically important to understand it as we look to the future, and by focusing on the role of information we can gain new insights about the past.

Our overriding aim in this paper is analytical: we provide a theoretical framework within which to understand the role of information – past, present, and future – in the politics of social protection. We show how the level of information, and who can share in that information, shape markets for insurance, support for public provision of insurance, and political conflict over the distribution of the costs and benefits. We also briefly explore the implications of our argument with three types of evidence that speaks to the effects of Big Data. First, we present two illustrative case studies: one of the reform of the unemployment insurance system in Sweden, and one of the increasing use of individual information to price-differentiate in life and health insurance markets. Second, we consider the expansion of private markets in life insurance. Life insurance is an area that works similarly to health insurance, and we show that the growing availability of health information has facilitated the expansion of life insurance markets, tempered by a strong political Left. Since life-insurance has never been provided through the state (except for some modest widows' pensions), it offers a window into the possibilities of private insurance. Finally, we explore a policy area – unemployment insurance – that has mostly remained public yet shows signs of polarizing support as information about risk improves – even after controlling for the variance in actual risk.

2. State of the literature

Akerlof's seminal 1970 *QJE* article lays out a key reason for the breakdown of markets: asymmetric information and the associated problem of adverse selection. Rothschild and Stiglitz (1976) and Stiglitz (1982) develop the logic for insurance markets, with more recent extensions summarized in Boadway and Keen (2000), Przeworski (2003), and Barr (2012). In these models individuals know their risk-types, but insurers do not. Market failure occurs when plans that are directed at those with low risks are picked up by those with high risks, raising prices, and driving out the good risks. In Akerlof's model, this "adverse selection" logic ends in a market only for bad risks, or "lemons."

There are three limitations to the standard economic analysis. First, and most obvious, it does not capture the *politics* of social insurance. While economists are usually satisfied to propose that market failure functionally requires (and justifies) government intervention, public provision will be opposed by those with the lowest risks – such as the young and healthy in the case of healthcare. They may prefer to go entirely uninsured in a private market to paying into a public system where they subsidize those at high risk. Yet, for the same reason, a political majority may prefer such a system to reduce their own costs. When they do, majority demands become the driver of public provision, not the "need" to overcome market failure (we will show this more formally below).

Second, the assumption in standard models that risk is only known to buyers is increasingly untenable. Low-risk types have an incentive to share their information with insurers to reduce their premiums, and better access to independent collection and validation of information is enabling such sharing to be credible. If credible information sharing is feasible, "separating equilibria" with highly segmented risk markets are possible. Moreover, if markets are feasible, a majority may prefer a market-based system. This is true if we assume that private insurance is not less cost-effective than public provision, and that the risk-distribution is right-skewed. The latter is normally the case, as we will discuss.[1] This will not necessarily lead to a private system, but it opens up the possibility of majority coalitions that will introduce more differentiation in the public system.

Third, the standard model focuses on asymmetric information without considering the effects of differences in the *level* of information. Even when risks such as unemployment are uninsurable in private markets, information will shape the structure of support for public spending. Since

[1] The former may or may not hold. We make the assumption to identify the effect of information. It is discussed below.

those with low risks subsidize those with high risks, public risk pooling is always strongly redistributive. But it is only when the risks are known that this becomes a source of political conflict. More information therefore challenges the cross-class “solidarity” that characterized the politics of social insurance in the postwar period. Again, information has political consequences.

Our model makes two contributions. It adds *politics* to economic models of insurance, and it adds the role of *information* to the scholarship on welfare state politics. The latter literature has emphasized how peoples’ position in the economy affects their exposure to risk and consequently their preferences for insurance. Garrett (1998) and Rodrik (1998) show how economic openness can be a source of risk, and Scheve and Slaughter (2001) and Walter (2010) how it may shape preferences; Margalit (2013) considers how experience with economic shocks affects preferences, while Mares (2003) examines the effects of risk exposure across industrial sectors; Moene and Wallerstein (2001) look at the relationship between income and demand for insurance; Iversen and Soskice (2001) introduce the role of skills, and Rueda (2007) considers divisions between secure insiders and insecure outsiders. Strikingly, none of these contributions considers information as an independent causal variable. The focus is exclusively on determining who is at risk and how this shapes people’s preferences. We instead show that the distribution of preferences changes with information, even when the distribution of risk is constant.

Our argument complements a burgeoning new literature on the consequences of expanding private alternatives to the public systems (Busemeyer and Iversen 2014; Cammett, Lynch, and Bilev 2015; Gingrich 2011; Gingrich and Ansell 2012). But while this literature explores the interplay of marketization and politics, we model it as a function of the nature and availability of data on risk. To our knowledge, no existing model does that.

3. The model

We present the argument in four steps: (i) we begin by introducing the classic asymmetric information case and show that it leads to majority support for public provision under most realistic assumptions; (ii) we then turn to the symmetric information case and show that when information is plentiful and can be credibly shared with insurers, a majority is likely to prefer market provision (or a public system that mimics markets); (iii) next, we show that when market solutions are blocked, whether for political or economic reasons, preferences over public provision will polarize with information; (iv) finally, we consider the role of government partisanship in regulating markets and information.

The model is developed from the perspective of individuals' demand for insurance, and it will be readily recognizable to readers familiar with canonical models of demand for public insurance in political science. For readers familiar with the standard economic model of private insurance markets, Appendix A shows the connections between that model and the one presented in the text. For every result, Appendix B shows that the insurer's budget constraint is always satisfied

3.1. Basic setup

We assume that people are looking one period into the future and decide how much of their current income to spend on insurance against the risk of losing that income in the next period (as a result of illness, unemployment, etc.). The model uses log utility to capture risk-aversion (RRA=1) in a simple and tractable manner. Specifically, the (von Neumann–Morgenstern) expected utility of individual *i* is defined as:

(1) $$U_i = \ln\left(y_i - c_i\right)\cdot(1-p_i) + \ln\left(k_i + b_i\right)\cdot p_i\,,$$

where $y_i > 1$ is income when in the good state, c_i is the cost of insurance, p_i is the risk of losing income, b_i is the insurance benefit in the bad state, and k_i is a pre-transfer income from private sources when in the bad state. If the bad state is one in which the individual is unable to work, k_i can be understood as non-labor income from savings or other assets ("self-insurance").

We initially assume that *i* knows everything there is to know: y_i, c_i, p_i, k_i, and b_i, and we define c_i as the share, π_i, of income that goes to paying for insurance, so that $c_i = \pi_i \cdot y_i$. If insurers also had this information they could offer insurance plans for each risk group, using premia by those in the good state to pay for benefits of those in the bad state. Ignoring administrative costs, as well as any markups (which are irrelevant for our results), the insurer breaks even when the insured individual benefit is:[2]

$$(2) \qquad b_i = \frac{\pi_i \cdot (1 - p_i)}{p_i} \cdot y_i ,$$

where $\pi_i \cdot (1 - p_i) / p_i$ is the income replacement rate, and $-(1 - p_i) / p_i$ is the slope of the "fair-bet" line in the standard economic model of insurance, which is shown in Appendix A.

Since *i* is risk-averse, he or she will purchase enough insurance to equalize expected income across the two states, which is simply the value of π_i that maximizes (1):

[2] To see this note that for each insured, the expected payout by the insurer in each period is $p_i \cdot b_i$, while the expected premium received in each period is $(1 - p_i) \cdot \pi_i \cdot y_i$. Across a large insurance pool, expected payouts and premia will be equal to actual payouts and premia, and the insurer will break even when $p_i \cdot b_i = (1 - p_i) \cdot \pi_i \cdot y_i$, which yields equation (2).

(3) $$\pi_i^* = p_i \cdot \left(1 - \frac{k_i}{y_i}\right) = p_i \cdot (1 - s_i),$$

where s_i is non-labor income in the bad state as a share of labor income in the good state. Unsurprisingly, the higher the risk of losing income the greater the share of income spent on insurance. Higher labor income increases demand for insurance (as for any normal good), but higher non-labor income reduces demand (because it provides self-insurance). If the latter comes from savings out of the former, demand will depend on the savings rate, which tends to be rising in income. Since the relationship between income and savings is not important for our purposes we assume that the savings rate is constant: $s_i = s$.[3]

With these basic elements of the model established, we now introduce variation in information about individual risks. We begin with the classic case of asymmetric information, where the buyer of insurance is informed but the insurer is not. We then ask what happens when information is shared with insurers, and we finally consider the case where neither buyer nor insurer is informed.

3.2. The asymmetric information case

Insurance markets would not be problematic if individual risks were observed by insurers. But if insurers do not have individual information about risks, they will only know the mean risk in the pool of insured, $\overline{p}$, which they can infer from the share of insured individuals who collect

[3] Recent work by Ansell (2014) and others emphasize the role of non-labor income for preferences, and our model is entirely consistent with this work.

insurance. With asymmetric information the benefit received by *i* now depends on $\bar{p}$ instead of p_i [4]

$$(4) \qquad b_i^{"} = \frac{\pi_i \cdot (1-\bar{p})}{\bar{p}} \cdot y_i,$$

and the preferred level of insurance is a function of *both* individual risk *and* average risk:[5]

$$(5) \qquad \pi_i^{**} = p_i - (1-p_i) \cdot s \cdot \frac{\bar{p}}{1-\bar{p}}.$$

At the price and replacement rate implied by (4) and (5), will individuals buy insurance? The answer depends on their own risk relative to the risk of others. Clearly, those with p_i above $\bar{p}$ will find the pooled insurance plan an unambiguously good deal; those with a p_i below $\bar{p}$ may or may not. This is because for these individuals there is an additional cost of insurance, which is the implied subsidy to those at higher risk. This cost is a function of the composition of risk in

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[4] For each individual expected payout is now $\bar{p} \cdot b_i$ and the expected premium is $(1-\bar{p}) \cdot \pi_i \cdot y_i$. In equilibrium the two must be equal, which gives (2). The process by which the equilibrium is reached is explained below.

[5] This is the value of π_i that maximizes equation (1) when the replacement rate is $\pi_i \cdot (1-\bar{p}) / \bar{p}$ instead of $\pi_i \cdot (1-p_i) / p_i$. Note that we assume for equation (5) that insurers cannot infer the risk of an individual from the amount of insurance purchased by each individual. We show in Appendix A that this assumption is satisfied if insurers do not know the total amount of insurance bought by each individual from all insurers, and/or if they do not know individual income or degree of risk-aversion, which will affect demand. In either case it prevents an insurer from offering a “cheap” plan that will only be taken up by low-risk types.

the pool of insured, so each individual's decision to buy insurance depends on the decision of others. It is therefore the outcome of a network game.

Specially, an individual will buy insurance if:

$$\text{(6)} \qquad \begin{array}{l} \pi_i^{**} > 0 \\ \Downarrow \\ p_i > \dfrac{s}{1/\overline{p} - 1 + s}. \end{array}$$

The equilibrium is found where the expected mean risk in the insured population, $\overline{p}^e$, is equal to the actual mean risk:

$$\overline{p}^{p_i > q} = \overline{p}^e,$$

where $\overline{p}^{p_i > q}$ is the mean risk in a pool of people who are above a critical threshold, *q*, which is given by equation (6) above. This is also the point at which the insurer breaks even (see Appendix B for a proof).

The logic is illustrated in Figure 1, which uses an example of an even distribution of risk in the interval [0, .5], and *s*=.5. If everyone buys into the insurance plan, so that coverage is 100 percent (recorded on the right *y*-axis), the expected $\overline{p}$ is .25. At this implied "price" only those with individual risks above .14 (given by equation 6) would buy insurance, which is here equivalent to 71 percent of the population. As low-risk types exit, the insurer will no longer break even and the average risk in the insurance pool rises to $\overline{p} = .33$. This becomes the new expected risk, as indicated by the dotted arrow. This "lemons" logic continues until the line that maps expected onto actual risks intersects the 45-degree line (the dotted arrows). At this point the equilibrium of the game is reached, which in our example implies a small majority (57 percent) buying private insurance.

The example shows that Akerlof's "lemons only" conclusion is too gloomy since many people might end up with at least some private insurance.[6] Yet the outcome is unambiguously inefficient, since we know that *someone* at low risk will always find it preferable to opt out of the private insurance plan even though they would buy insurance in a world with complete information.

Economic analyses end here, and public provision is "explained" as a solution to a problem of private under-provision. Yet efficiency is *not* what brings a public system about politically; nor is it demand from the completely uninsured. Instead, it results from a majority supporting a public system where low-risk types are required to contribute to the pool and hence subsidize those at higher risk (whereas in a private system they will opt out). In other words, it is a matter of majoritarian coercion.

This is easy to see in our example where the individual with the median risk (equal to .25) would spend 3.9 percent of her income on insurance in the private market and get a replacement rate of 6.7 percent in the case of income loss.[7] By contrast, in a public system with a proportional tax,

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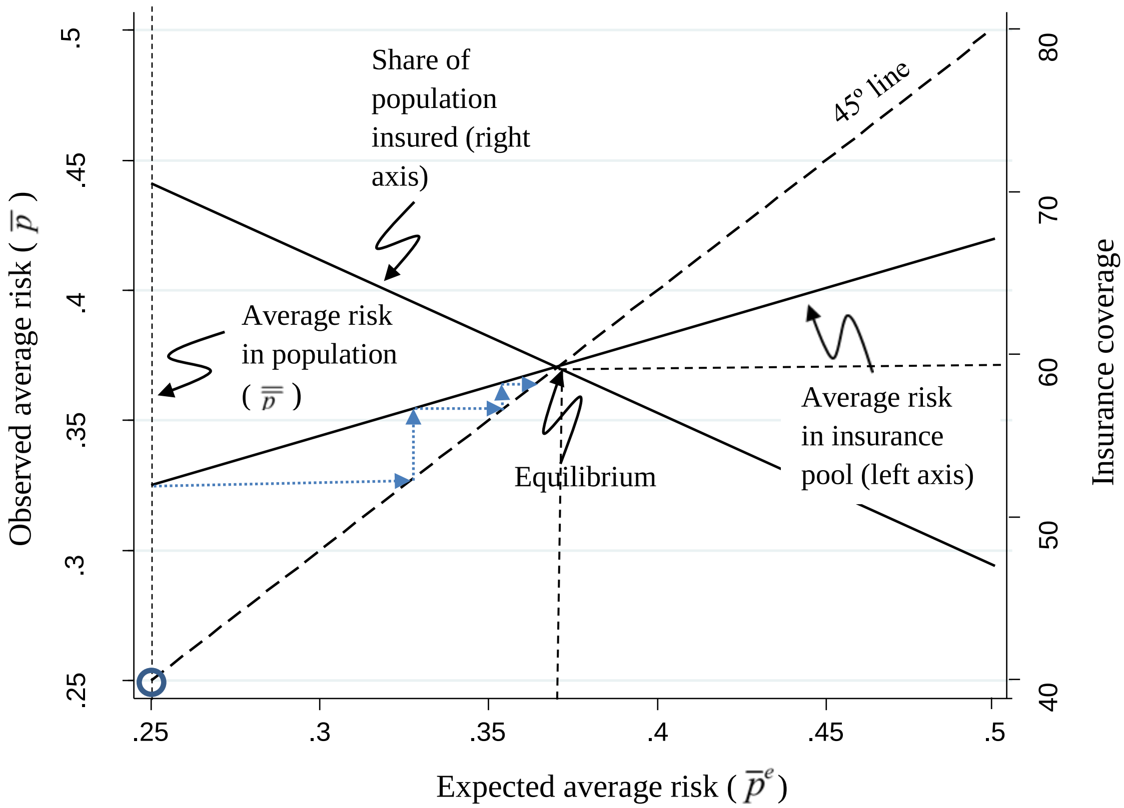
[6] Akerlof's market for "lemons only" is where the average-risk line meets the 45-degree line at the highest level of risk. In Akerlof's model this holds since he assumes that people are risk-neutral. Our model assumes risk-averse agents.

[7] The median risk is .25 and the average risk in the pool is .36, when in equilibrium (see Figure1). This gives the optimal spending from equation (5). The replacement rate can then be calculated from equation (4).

the median voter would choose a 12.5 percent tax rate and get a 37.5 percent replacement rate (which would exactly equalize net income in the two states).[8]

Figure 1: Equilibria in the private insurance network game with private information



Note: simulations assuming s=.5 and $p_i = [0, .5]$

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[8] Net income in the good state is $(1-.125)\cdot y_i = .875\cdot y_i$ and net income in the bad state is $(.5+.325)\cdot y_i = .875\cdot y_i$, ($s$=.325 and $\pi_i = .325$).

3.3. The symmetric information case

Akerlof and Stiglitz did not discuss the case of symmetric information since they were interested in exploring the consequences of private information. But the symmetric information case is important to our story, and it comes in two varieties. In the first *neither* buyers nor sellers have individual information about risk (low information). In the second *both* do (high information).

3.3.1. *Symmetric but low information*

In the case of *no* individual information, people will have to rely on the same aggregate information as insurers. Each person will have to form an expectation of their risk based on the observed number of unemployed, disabled, sick, and so on. In our model this is simply the mean risk in the population: $p_i^o = \bar{\bar{p}}$, where p_i^o is *i*'s observed level of risk and $\bar{\bar{p}}$ is the overall population mean (as distinct from the mean among the insured, $\bar{p}$). Since everyone has the same expectation, including the insurer, and since $\bar{\bar{p}} \cdot (1-s)$ is everyone's preferred spending (from equation 3), $\bar{p} = \bar{\bar{p}}$ is an equilibrium. In Figure 1 this special case is indicated with a circle at the bottom left corner (which is on the 45-degree line).

In the real world, there may be no examples of such a complete lack of information, but the case is instructive nonetheless. The reason is that uncertainty reduces the variance in policy preferences: whereas the range of preferences in the private information case is $p_i = [p_{\min}, p_{\max}]$, in the case of uncertainty the range is $p_i^o = [p_{\min}^o, p_{\max}^o]$ where, again, p_i^o is observed risk. The latter will be narrower than the former, which can be modeled as a simple Bayesian logic:

(7) $$p_i^o = \alpha \cdot p_i^s + (1-\alpha) \cdot \bar{\bar{p}}$$

where p_i^s is a noisy signal drawn from a distribution that is centered on the individual's true risk (p_i) and α is a measure of the "precision" of that signal, which in our model equals the private information available to *i*.[9] With no information ($\alpha = 0$) *i* only observes the population mean, $p_i^o = \overline{\overline{p}}$, and the range is therefore zero. At the other extreme, with complete information, $p_i^o = p_i$, the range equals the difference between those with the lowest and the highest risk. A very simple way of stating the general insight is that *class conflict increases with information*. Behind the veil of ignorance everyone can agree that insurance is a good thing; otherwise they clash. Even if markets are not feasible, information shapes politics.

3.3.2. *Symmetric and high information*

The final, and important, case is where information is plentiful and can be shared between buyer and provider. Even when legal privacy protections limit the ability of insurers to acquire individual information, which is usually the case of medical records, insurers may not need to unlock private information – people may choose to share it voluntarily. The example in the introduction of using monitoring devices to reduce insurance premia provides the intuition for why they might do so

This logic applies to the important area of private health data where the level and credibility of information has vastly improved. There are three related forces behind this trend. First, the

[9] We can think of the "precision" of the signal as the accumulated information over some period of time. In the case of unemployment risks, signals are both an individual's actual experiences of unemployment and observed unemployment in the industry, occupation, or network to which the individual belongs. A formal proof for (7) can be found in Iversen and Soskice (2015), Appendix B.

general advance of medicine has made diagnostics much more detailed and reliable (Shojania et al. 2003). Second, the explosion in the number and variety of tests that can be done by certified labs has made it possible to share this information credibly. DNA diagnostics in particular promises to offer an order of magnitude more information about health risks than in the past. Finally, computing power combined with AI has made it possible to classify individuals in risk groups much more accurately than in the past.

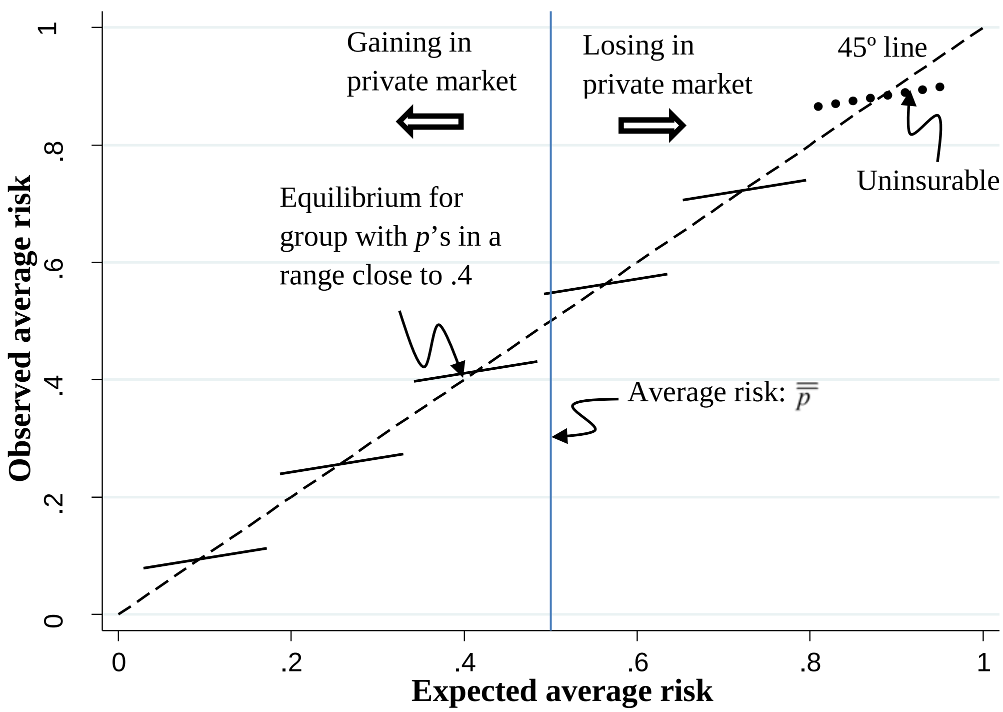
The fact that individual information can be acquired by, and credibly shared with, would-be insurers ameliorates the asymmetric information problem and opens the possibility that insurance can be provided efficiently through the market. For each group with identical risk profiles there would now be a separate insurance plan with its own cost and replacement rate, corresponding to a point on the 45-degree line in Figure 1 (in Appendix A this would be equivalent to the three equilibria: x, y, z). More realistically, we can allow for some modest risk-heterogeneity within groups that is unknown to the insurer. As long as insurers have enough information to distinguish members of different groups, we would get a series of distinct (pooled) equilibria/insurance plans as illustrated in Figure 2. The analysis of each one of these equilibria follows exactly the same logic as set out in Figure 1.

In this brave new world of near-complete information there would be a well-functioning market for the "creampuffs" – people with low risks that insurance companies crave. In fact, anyone below the mean ($\overline{\overline{p}} = .5$ in Figure 2) would be better off in such a world, assuming (as before) that private provision is no more or less efficient than public provision.[10] This is because

[10] This is of course an issue of considerable debate. The function of the assumption here is to help us identify the effect of information on the direction of change in distributive politics.

everyone with below-average risk subsidizes those with above-average risk in a public system. Another implication is that those with the highest risk, who also tend to have the lowest incomes, may be unable to afford any private insurance tailored to high risks.[11] For example, low income people with serious risk of diabetes may be unable to effectively insure against that risk if there is no pooling with lower-risk groups. We have indicated such non-insurability with the dotted line in Figure 2. In contrast to the low information case, those who are left without insurance are now only those at high risk.

Figure 2: Equilibria in the private insurance network game with shared information



[11] The link between risk and low income is thoroughly documented in the medical literature (Chen and Miller 2013).

Note that the possibility of credible information-sharing has implications even for those who want to protect their privacy. The reason is that “refusers” will be placed in a high-risk group with high premiums, and everyone in that group with risks below the group average has an incentive to divulge their information to reduce their cost. If they do, the same is true for those below the average in the remaining group, and this process will continue until all the “lemons” are called out. This is Akerlof’s logic in reverse because the result will now be a segmented private market for risk where all information is common, and with an uninsurable group relying entirely on the (likely underfunded) public system. It is clear from this analysis that privacy laws are *not* a remedy for the problem.

Would there be majority support for privatization? On our assumptions, the answer is *yes* as long the risk distribution is right-skewed. This is unambiguously true in the case of health risks,[12] and Rehm (2016) shows that this is ordinarily also true in the case of unemployment risks. In an up-down vote, self-interested voters would therefore support privatization. Again, this conclusion is only true in a world of complete and shared information, and we are not in such a world. At the same time we are almost certainly moving towards this world, and as we do, the public system will become increasingly contested and fragile.

3.4. The role of regulation and government partisanship

Our partisan conjecture is simple and echoes long-standing arguments about partisanship (Esping-Andersen 1990; Huber and Stephens 2001). Since left parties tend to represent low-

[12] This is because almost all health risks are concentrated among the poor and the elderly. While there is no direct data on risk, health spending is highly concentrated. In 2009 about half of US healthcare spending went to only five percent of the population (National Institute for Health Care Management 2012).

wage, high-risk groups, while the opposite is true for right parties, we expect left-leaning governments to try to inhibit the development of private insurance markets and shore up support for the public system. This may also be true for some types of insurance that are not provided publicly, such as life-insurance, if such markets are "fungible" to other areas that *are* public, such as health insurance. Life insurance companies are often also health insurance providers, and the former will build up expertise and organizational capabilities in the health insurance market.

Governments affect private insurance outcomes via two main mechanisms. One is a simple crowding-out effect. By promoting public spending on social insurance and mandating people to pay into it, the scope for a private market is diminished. Private insurers can offer attractive plans to individuals, but since people opting out of the public system face a double payment problem there is little demand. Yet, whether there are "discounts" for people who do not use the public system, or even direct tax subsidies for acquiring private insurance, is of course a political decision (as we will see in our Swedish case study below, politics has favored privatization).

The second mechanism is to impose non-discrimination clauses on the private insurance industry. Insurers may have the necessary information to offer differentiated plans, but they may not be permitted to use it. In this case the analysis is indistinguishable from the asymmetric information case in Figure 1: adverse selection will undermine markets. An example is the US Genetic Information Nondiscrimination Act of 2008 (GINA), which prohibits insurers from using individuals' genetic information to price-discriminate against otherwise healthy individuals. It does not however prohibit such discrimination in life insurance, disability insurance and long-term care insurance markets, and US states have considerable discretion in the implementation. Nor does GINA apply to non-genetic information. Again, regulation is always a political choice.

3.5. Summary

Our information argument is summarized in Table 1. We distinguish two dimensions of information: (i) the level of individual information, and (ii) whether it can be credibly shared with insurers. If private information cannot be credibly shared, markets will be inefficient as low-risk types exit and push up the price of insurance for all others. In this case, a majority will typically have an interest in a public system. With low information, support for a highly risk-redistributive public system may be very broad, as everyone has to assume that they may be beneficiaries of the system. We call this the solidaristic welfare state outcome.

When information can be credibly shared with insurers, however, private markets become feasible. Credible information sharing is usually accompanied by high information, and this opens the possibility of a segmented private insurance market where each risk group is offered its own plan (the size of each pool will depend on the detail of the information available as well as the economies of scale by insuring more people under the same plan). When tailored private insurance is feasible, those with risks below the mean will prefer private provision, and with a right-skewed distribution of risk, this will be a majority.

Broadly speaking, our argument implies that the information revolution results in pressures toward more market provision (the arrow in Table 1). Yet these pressures will be tempered by left governments using measures such as "price non-discrimination" clauses to rule out private markets. Highly correlated risks may also prevent markets from emerging, or at least require a "payer of last resort" role for the state. When markets are blocked for either reason, increased information will cause polarization in preferences over the level of public provision and the distribution of the costs. This is the contested welfare state outcome in Table 1.

Finally, it stands to reason that markets can be preempted by allowing greater differentiation in the public sector. In this case, one can think of private markets as having an effect through "shadow prices:" the public sector mimics the private in terms of choice and prices. This would imply policies that allow more differentiation and choice in the public system, use of credits for supplementary private insurance, cut in benefits for high-risk groups (such as disallowing payment for procedures for obesity), and introduction of high co-payments (which are highly regressive). We have indicated this possibility using parentheses around "private" in the high-segmentation cell.

Table 1: Information and social insurance

		Credible information sharing?	
		No (Asymmetric information)	Yes (Symmetric information)
Level of information	Low	Solidaristic welfare state	[Pooled private insurance]
	High	Contested welfare state	Segmented (private) insurance

3.6. Caveats

Our model makes several assumptions, two of which are likely more controversial than the others. First, we assume that private and public systems are equally cost-effective, yet public single-payer systems may offer economies of scale and simplicity that make private provision uncompetitive. Second, we assume that agents have no other-regarding preferences, yet norms of fairness may drive even those who might benefit in a private system to support a public system. We agree that both assumptions can and should be subject to research and debate. But our aim is to show that more information can make markets viable where they did not exist previously, and solidarity may be severely tested when the costs and benefits of public provision become more transparent. The data revolution has unleashed forces that our model identifies, even as it ignores counter-vailing forces of stability already identified in the literature.

An objection that speaks more directly to the model is that we all face uninsurable risks. Ultimately people die, and most people go through shorter or longer periods of illness as they reach the end of life and need intensive care for which there may be no private insurance. Private care plans (which are really insurance against disability) all have time limits (usually three years), which pushes the tail risks onto individuals, their families, or the state. It is estimated that one third of Americans will end up needing long-term nursing care and a full two-thirds of these will eventually fall back on Medicaid to cover their costs as private savings run out (NYT, June 13, 2017). This may convince a majority to support a role for the state as a "payer of last resort". Note, however, that this argument relies on a logic we have already identified, namely that lack of information about risks (here ones that lie far into the future) leads to support for public insurance. Yet, even here, the veil of ignorance is continuously being lifted for conditions that most people only face in their old age (notably dementia, including Alzheimer's). As this happens, those blessed with good genes may be less enthusiastic about "last resort" programs such as Medicaid.

4. Empirics

In this section, we explore the model's key mechanisms, using four short empirical illustrations. We provide first-pass tests of two hypotheses following from the model: (i) *as information improves, and as such information can be credibly shared with insurers, private markets for insurance expand (H1)*; and (ii) *as individual information improves, preferences over the level of public provision polarize* (*H2*).

4.1. Individualization of life and health insurance

Our first case study is from the health insurance industry in which the use of technology to track and incentivize particular consumer behavior is one innovation frontier. As mentioned in the introduction, premiums that are based on behavior are already very common in the car insurance market, and life and health insurance companies increasingly offer them as well. It is a prime example of credible information-sharing for the purpose of individually targeted insurance plans, and therefore close to a situation where distinct plans are being offered on the 45-degree line in Figure 2.

In this business model, insurance companies worldwide team up with firms like Discovery Limited which develops wellness programs branded as "Vitality – A wellness solution that changes the way insurance works." Vitality uses data on consumer behavior, which are collected by fitness trackers (such as Fitbit, Jawbone, Misfit, Apple Watch) and transmitted to the company or insurer. Additional information, such as purchasing data, is sometimes collected as well. This detailed, constant, and instant tracking of consumers is useful for health and life insurance companies alike, as explained on the company's website:

> "Insurers traditionally use risk rating factors to access and underwrite risk. These include age, gender, socio-economic status as well as smoker status and medical history. These

> risk factors are mostly static and offer a limited view of a person's risk. A person's health behavior, however, provides a more accurate risk indication. Vitality, with its 17 years of wellness experience, data and understanding of wellness behavior, adds an additional dynamic underwriting rating factor. It takes into account the impact of chronic diseases and lifestyle factors, such as smoking, level of exercise, diet, alcohol consumption, blood pressure and cholesterol on a person's risk profile. By integrating Vitality with insurance products, we have developed a scientific and dynamic underwriting model that uses high-quality data about a person's health, wellness, credit card spending and driving behavior to assess their risk more accurately over time. This results in: better benefits, lower and more accurate risk pricing, better selection, lower laps rates, [and] better mortality and morbidity experience." (www.vitalitygameon.com)

Tracking devices ('wearables') are increasingly common in the life insurance market. And health insurance coverage plans relying on tracking devices – frequently in combination with workplace wellness programs that often perform health risk assessments and biometric screenings – are gradually rolled out as well. Policyholders with Oscar Health Insurance in the US, for example, receive a free step tracker and can earn up to $1/day for taking a particular number of steps. In a similar vein, health insurance company UnitedHealth and chipmaker Qualcomm have teamed up to develop a wearable device tied to a coverage plan that incentivizes health behavior by paying up to $4/day to a covered employee and their spouse if they reach certain targets.[13]

The new tracking systems have spread most widely to the life insurance market and include John Hancock Life Insurance (US), Prudential's Vitality Health (UK), AIA Australia life insurance and MLC On Track (Australia), and Generali (Austria, France, Germany). But they are equally useful for health insurers, and for now more than 100,000 employees at an undisclosed number of employers in a dozen US states are using wearables through UnitedHealth plans.

[13] Technological progress makes tracking devices ever more sophisticated. An example is the Kolibree toothbrush whose 3 axis accelerometer, 3 axis gyrometer, and 3 axis magnetometer can decipher detailed subtle movements in order to provide real-time feedback that gets transferred to one's smartphone via Bluetooth, from where it can be shared with a dentist. Of course, it could also be shared with a dental insurance company.

Yet, this is surely only the beginning. Big Tech is committing huge resources to the advancement of a new data-based health industry, using a variety of related strategies. Apple and Alphabet are developing new tracking technologies – for hearth rhythms, sleep patterns, circulation, and even sugar levels in blood – using wearables (including a smart contact lens), and microchips can now be implanted directly into the body to constantly monitor health and relay information. Alphabet has recently created a new research unit, called Verily Life Sciences, to develop these technologies using AI approaches to data analysis, and Microsoft's Healthcare NeXT is focused on collecting huge amounts of individual data from a variety of sources to cloud-based systems, including a virtual assistant that takes notes from patient-doctor meetings using speech recognition technologies (Singer 2017). As we will document below, the number of reliable tests that can be done by independent labs has also greatly increased over time, and these data can be combined with data from the new tracking algorithms to produce detailed profiles of individual health parameters with tremendous predictive power. The promise of "Personalized Medicine" is based on such individual information, and President Obama's Precision Medicine Initiative reads like an impassioned call for more data on people's underlying health risks – "including their genome sequence, microbiome composition, health history, lifestyle, and diet". As AI crunches these data, much greater risk-differentiation in insurance policies becomes feasible, which in turn expands the reach of markets and likely results in greater inequality in coverage and cost.

4.2. Unemployment insurance in Sweden

Unemployment insurance has historically been mainly a government responsibility, but more information may change the politics even in this domain. Developments in Sweden –the most unlikely of cases – can illustrate this. Until the mid-2000s Sweden had one of the most generous unemployment insurance systems in the world, with lax eligibility requirements and a 90 percent replacement rate. The system was largely tax-financed, and the modest fees paid directly to the unemployment insurance funds (UIFs) were leveled through an equalization fund, rendering the system highly solidaristic (Holmlund and Lundborg 1999). At the same time, the administration of the UIFs was delegated to unions (known as a "Ghent" system), which gave unions de facto power to organize workers (Clasen and Viebrock 2008; Rothstein 1992). As a result, almost every Swede was a member of a union and its affiliated UIF (even though membership was formally separated in most cases).

Yet, this system was significantly overhauled from 2006-8. A center-right government cut replacement rates, tightened eligibility requirements, and reduced the maximum benefit ceiling. Crucially, a greater share of the financing burden was shifted to the UIFs, and fees were allowed to vary by the unemployment rate in each UIF with no obligation to pay into the equalization fund (Clasen and Viebrock 2008). This burden-shifting was used to partially finance an across-the-board tax cut (Kjellberg 2009).

The most obvious consequence of the reforms has been a sharp divergence in insurance fees. Because Swedish unions are segregated by occupation and socioeconomic status, and because unions serve as gate-keepers for entry into the UIFs based on detailed information about workers' education and current and past employment, differences in occupational unemployment rates directly translate into differences in fees.

Yet the reforms would probably not have been politically sustainable if not for another, parallel, development: a massive increase in supplementary insurance plans offered by unions in partnership with private insurance companies. These private top-up plans fill the sometimes large gap in replacement rates for higher-income workers. This private tier of the system has been enabled by a combination of the “voluntary” character of the Ghent system, high segregation of unions by occupation, and a growing divergence of risk by occupation. UIFs represent increasingly distinct risk pools with clearly demarcated boundaries, corresponding to the situation illustrated in Figure 2 above. In 2009 the unemployment rate among hotel and restaurant workers, for example, was 9 percent, while it was only 2 percent on average for the entire Saco area (Kjellberg 2009, 492).[14] These are differences that have been magnified over time as a result of technological change favoring high-skill groups (Autor, Levy, and Murnane 2003).

It is the unique interaction of information and Swedish labor market institutions that enabled this development. It is the the fact that unions organize increasingly homogeneous risk pools, combined with the fact that they have the information and power to exclude workers who do not fit into the pool which renders the system feasible. To become a member of an UIF workers have to not only declare their occupation but demonstrate that they have the formal qualifications required for a particular trade. As gate-keepers Swedish UIFs have thus enabled the emergence of private markets in unemployment insurance by providing reliable information about individual unemployment risks. It is a historical “coincidence” that Swedish UIFs are differentiated by skills (augmented by skill biased technological change) and that UIF have the power to enforce such differentiation, but it is a dramatic and surprising illustration of how information about risk can enable insurance markets to grow.

[14] Saco (the Swedish Confederation of Professional Associations) represents more than half a million white collar members (teachers, architects, economists, lawyers, engineers, doctors, and scientists, etc.) in professional associations.

The Swedish case also speaks to the *politics* of private insurance. The reforms were initially fiercely opposed (Gordon 2015), but they have proved resilient. Private insurance holders have risen from 200,000 in 2002 to an eye-popping 1.8 million in 2010 (Davidsson 2013). These workers are overwhelmingly organized in professional white-collar confederations Saco and TCO,[15] and because they cover mostly low-risk workers, their plans are inexpensive despite a generous 80 percent replacement rate (OECD 2015a). It is reasonable to assume that those covered by private plans have been net beneficiaries after factoring in the tax cut, and if we add to their ranks older workers whose jobs are almost guaranteed by the Law on Employment Protection (Kjellberg 2009), the total number that has gained likely exceeds half of the Swedish labor force.

At the other end of the risk distribution, workers are opting out of unemployment insurance altogether. All UIFs that insure the most vulnerable workers have seen a dramatic outflow of members, leaving a large group of uninsured workers dependent on minimal social assistance in the event of unemployment (Kjellberg 2009). These workers, who are at high risk of falling into poverty (OECD 2015a), correspond to the uninsured high-risk group in Figure 2. In the solidaristic public system their insurance was subsidized by those at low risk; in the new quasi-private system they cannot afford to pay.

Swedish unemployment insurance is still not a fully private system. This is because the government continues to provide subsidies for the UIFs and would have to step in to guarantee benefits in the event of a major economic crisis that would threaten UIF insolvencies. Although the system now involves private insurance companies in a central role, the state is still a payer of

[15] TCO (the Swedish Confederation of Professional Employees) represents more than a million white collar employees.

last resort – a fact that is helping to keep premia low. This fact points to an obvious moral hazard problem because insures may not charge enough to build up sufficient reserves for large economic downturns, expecting to be bailed out. Even if private plans are not bailed out, workers in these plans are sufficiently powerful politically that they can reasonably expect the government to keep them afloat in the event of a major crisis. This is not unlike the role of Medicaid in the American health system, stepping in when private care plans run out.

4.3. Information and private market penetration: life insurance

To explore the effect of information on private market penetration (H1), we turn to information about health and the development of life insurance markets. Apart from modest programs for survivor's (widow's) pensions, the public system offers no life insurance. This is therefore an obvious area of potential private expansion as more medical information becomes available that can be credibly shared. We expect that better information regarding health risks leads to larger life insurance markets.

Our *dependent variable* is life insurance market penetration measured as a ratio of direct gross life insurance premiums to Gross Domestic Product (GDP). The measure is developed by the OECD and "represents the relative importance of the insurance industry in the domestic economy" (OECD 2015b). We have data covering 22 advanced economies for about 1983-2013. (Appendix D provides more details on the data, as well as methods, variables, and results).

The key *independent variable* is private information that can be credibly shared with insures. We do not, of course, have direct access to private information, but such information is reflected to some extent by the availability of diagnostic tests. Accurate tests by independent labs are exactly what insurance companies need to distinguish risk groups, and such tests – based on blood, saliva, urine, tissue, and increasingly genetic samples, in addition to CT and MRI scanning – have become much more common, accurate, and affordable. A striking example is the cost of sequencing the human genome, which has dropped from about 300 million dollars in 2001 to less than 1000 dollars in 2014. The number of personalized gene-based diagnostics and treatments available in the US has correspondingly risen from 13 in 2006 to 113 in 2014 (Personalized Medicine Coalition, 2014). The number of standard tests on a simple penetration blood sample has increased from 130 in 1992 to 319 in 2014 (Pagana and Pagana 1992; Pagana, Pagana, and Pagana 2014).

We do not have nationally comparable data on the availability of diagnostic tests, but we do have an authoritative and widely used indexing of diagnostic tests by the National Library of Medicine. It maintains a list of 27000 or so "Medical Subject Headings" [MeSH]" (Coletti and Bleich 2001) that are designed to map the entire biomedical field based on English-language academic journals. The MeSH classification includes a hierarchical tree structure where one sub-branch indexes terms related to "Diagnosis" (E01). We use the entries in this diagnosis-branch to chronicle the development of diagnostic tools since the 1970s.[16] For example, in 1971, there were 277 index entries; there were 450 in 1981, 600 in 1991, 701 in 2001, 914 in 2011, and 1067 in 2014.

To get variation by country we exploit the fact that good diagnostics is a necessary condition for all modern medical treatment. Ipso facto, effective treatment is a sufficient condition for accurate diagnostics. This is a useful insight for our purposes because the World Health Organization

[16] Another standard source on medical tests known as Mosby's Diagnostic and Laboratory Test Reference yields essentially identical results.

(WHO) collects detailed data on mortality by cause, and it calculates a "Potential Years of Life Lost" (PYLL) estimate for each major cause of death (cancer, cardiovascular deceases, AIDS, and so on). PYLL is the difference between how long people diagnosed with a particular disease actually live and the average life expectancy (weighting deaths occurring at younger ages more heavily).[17] PYLL is available for a broad set of 22 advanced countries from 1983 to 2013.[18] To derive the indicator, we regress the MeSH-data on the PYLL series, along with a set of control variables, and use the predicted values as a measure of information.

As expected, there is a strong negative relationship between PYLL and the number of diagnostic tests, and if we assume that in countries where people die earlier from particular diseases have fewer diagnostic tests available then this will limit the scope for the life insurance industry to flourish because it depends entirely on an established infrastructure of labs, testing technology, and expertise. A life insurance candidate getting a health exam is literally proving fewer risk indications in one country than in another. This makes it harder for insurers to differentiate risk groups.

Our assembled data-set contains 486 country-year observations, covering 22 countries over the period from the early 1980s to the 2010s. Year-coverage varies by country, and we thus have an unbalanced cross-section time-series data-set. To focus on the dynamic nature of our argument and data, we estimate an error correction model (ECM) with panel-corrected standard errors and

[17] A low PYLL is however not a necessary condition for the availability of information because some diseases, especially soon after being discovered, are not treatable even if they can be accurately diagnosed (AIDS was a case in point).

[18] See Appendix D for details.

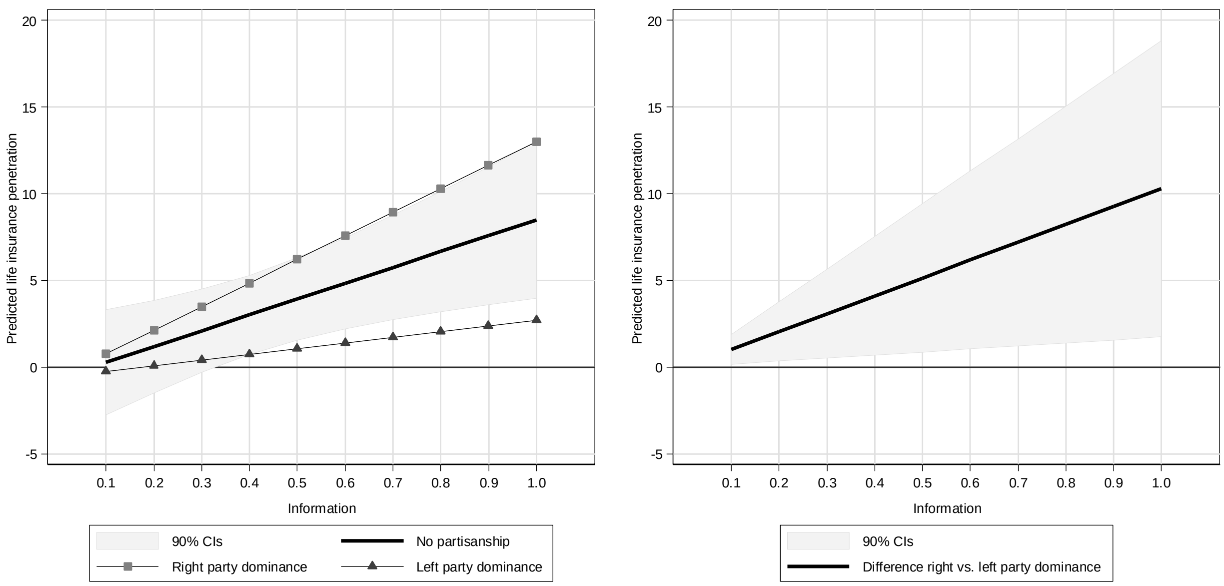
with an AR1 autocorrelation structure. The estimation results are illustrated in Figure 3 (detailed results are in Appendix D). We find that going from the lowest to the highest level of predicted information (0 to 1) raises life insurance market penetration by an average of about 4.5 percent in the first year, and by about 8 percent in the long run. This substantive effect is indicated by the solid upward sloping line in the left panel of Figure 3.

The left panel also includes separate estimates for countries with frequent left and right governments. The effect of information on life insurance penetration is much stronger in countries with frequent right governments (p95, top line), whereas it is muted in countries with frequent left governments (p5, bottom line). The right panel of the figure shows the difference between these lines (also based on Model (3)), which is very substantive at high levels of information, and statistically significantly different from zero throughout. Left governments (rightly) worry about the expansion of life insurance markets in large part because they could be trojan horse for expansion of private health insurance. While there are no readily available data on the regulation of the life insurance industry, a typical restriction is that insurance companies cannot use genetic information to set premiums.

The quantitative results are clearly only suggestive, but they lend support to our proposition that the increased availability of diagnostic testing has facilitated life insurance markets, barring regulations designed to counter this trend. .[19] Furthermore, the results are robust to the inclusion of a variety of controls, including the most plausible one: income (increases in income could drive up demand while simultaneously increasing research that might reduce PYLL).

[19] We get the same result by simply regressing market penetration on the number of tests.

Figure 3: Predicted life insurance penetration



Note: Simulations are based on Models (1) and (3) in Table D1 (Appendix D).

4.4. Information and polarization: the unemployment domain

Despite the Swedish reforms described in section 4.2., there is no robust market for private unemployment insurance, the main reason being the highly correlated nature of unemployment risks. This makes this domain an ideal testing ground for exploring our hypothesis H2 – that higher levels of information are correlated with more polarized attitudes even if private alternatives are not viable, and even if the underlying structure of risk does not change.

Our main *explanatory variable* here is information in the (un)employment domain. As in life insurance, the key challenge we face is how to measure private information. Our strategy builds directly on Equation (7) above, which shows that when actual risk is used to predict perceived risk there will be a regression towards the (national) mean as information (captured by α) falls.

We do not have individual information about actual risk, but we do have this information at the occupational level, and we therefore use the following estimating equation:

(8) $$p_j^o = \lambda + \alpha \cdot p_j^s + \varepsilon$$

where *j* indexes occupational groups, and α is our measure of information. With no information $(\alpha = 0)$, one could do no better in predicting the risk of any individual than the average unemployment rate. But when workers receive signals about their risks, α is larger than zero and rises in information. We can therefore use the estimated size of α as a measure of information.

The average signal, p_j^s, is measured as the annual occupational unemployment rates (OURs) for 75 distinct occupational groups – standardized across all years – in the Current Population Survey (Flood et al. 2015). We then assign these values to individuals in the US General Social Survey (GSS) (Smith et al. 2014), based on an occupational identifier. This allows us to estimate p_j^o using a subjective unemployment risk item that has been asked in 22 GSS surveys since 1977:

> Thinking about the next 12 months, how likely do you think it is that you will lose your job or be laid off – very likely, fairly likely, not too likely, or not at all likely? (Answer categories [reversed]: 1 Not likely, 2 Not too likely, 3 Fairly likely, 4 Very likely).

Information, α, is simply estimated for each year using Model (8), weighting by cell-sizes to reduce the variance of the estimator.

Our *dependent variable* is polarization with respect to preferences over unemployment insurance. For our purposes, one drawback of the GSS is that the survey items most closely tapping into attitudes toward unemployment insurance policies are not available very frequently, making it impossible to track developments over long time periods. We therefore use the following survey item to proxy these attitudes:

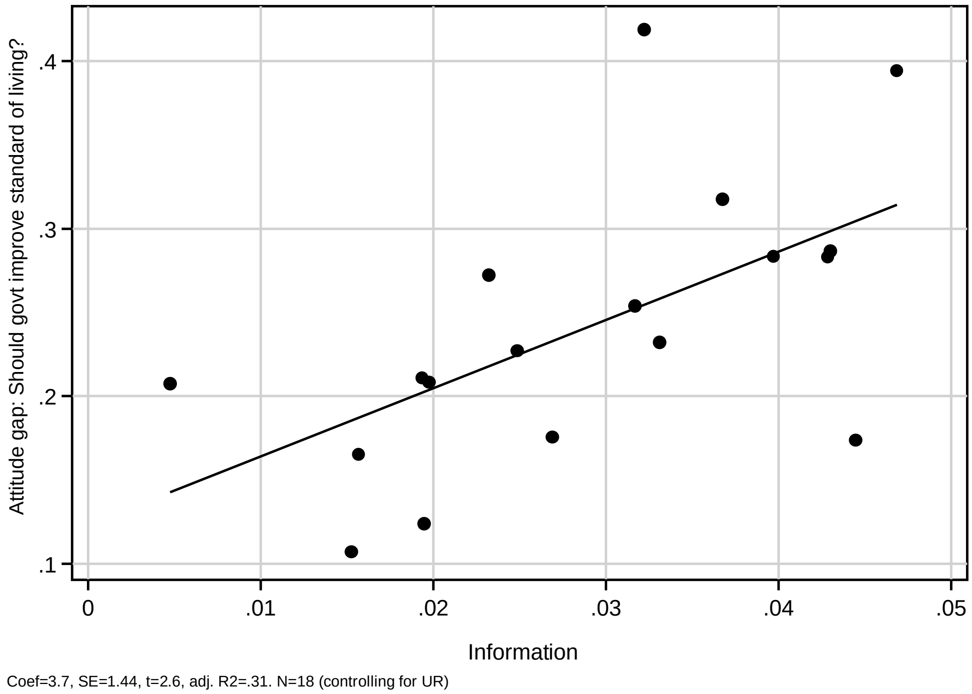
> I'd like to talk with you about issues some people tell us are important. Please look at [this card]. Some people think that the government in Washington should do everything possible to improve the standard of living of all poor Americans; they are at Point 1 on this card. Other people think it is not the government's responsibility, and that each person should take care of himself; they are at Point 5. [.] Where would you place yourself on this scale, or haven't you have up your mind on this? [Reversed scale: 5 Govt. action; 3 Agree with both; 1 People help selves]

The underlying assumption is that unemployment can lead to poverty, and that greater concern for unemployment therefore also leads to greater concern for reducing poverty. Indeed, the correlations between the above item and survey items tapping more directly into unemployment insurance attitudes are high.[20]

Figure 4 shows that, as expected from our model, polarization measured as the preference-gap between above- and below-average risk respondents is clearly related to our measure of information. It also shows the linear fit line, as well as the results from a regression of the gap on information and overall unemployment (see the note of the figure). There is a clear, positive, statistically significant correlation between information and contestation. This relationship holds if we regress polarization on information, while controlling for the observed unemployment gap between the two groups. So information drives polarization *independent of actual exposure to unemployment*.

[20] See Appendix B for details.

Figure 4: Information and attitude polarization (US)



5. Conclusion

The availability of information has rapidly increased from just a few years ago, and so has the number of tools to credibly share it. We have argued that this data revolution has the potential to revolutionizing the social welfare system. By providing good risks with an attractive private alternative to social insurance – an alternative that was historically not viable – it threatens the system of solidaristic public risk-sharing that emerged in the decades after the Second World War. Information can have consequences even when markets are not viable because it makes clear who benefits and who pays. When it comes to social insurance, ignorance about individual risks is a source of cross-class solidarity.

We close by briefly outlining four broad research frontiers. First, the logic we have proposed potentially applies to many policy areas we have not considered here. It is relevant to credit markets where the state plays a significant role, such as student loans and mortgages, as well as in areas where credit is used as an alternative to traditional insurance such as unemployment insurance (as illustrated by the Swedish case). Even quasi-private institutions that also play a role in social protection, notably collective wage-setting systems, are likely to be affected. Solidaristic wage bargaining in particular may depend on incomplete information because compression of wages serves as a form of insurance against downward mobility.

A second research frontier is the regulation of information and its use, notably price non-discrimination mandates. In a similar vein, policies aimed at reducing risk inequality could become more salient – ranging from retraining obsolescent skills, to physical education, mandatory prenatal diagnostics, or banning of trans fats or “gulp-size” sodas.

Third, we need more information about information. We have offered some evidence on the development of private information and how it shapes social policy conflict, but our proxies are rough. Observing private information, and how citizens acquire and use it, is – by definition – a very hard problem. But thanks to big data, this task soon will become a lot easier. We welcome innovative ways to measure empirically what is or can be known by individuals and insurers; a precondition for understanding the political consequences of the data revolution.

Finally, the transition to greater reliance on private insurance markets raises questions about how to insure the insurer. People could be left in a difficult situation if an insurer goes out of business. There is therefore a need for insurance against bankruptcies, which presupposes that the state accepts to be payer of last resort, similar to the one it plays in financial markets. This creates obvious problems of moral hazard by insurers themselves and will require more government regulation, and, indeed, more information. Data beget data, and de-regulation new regulation.

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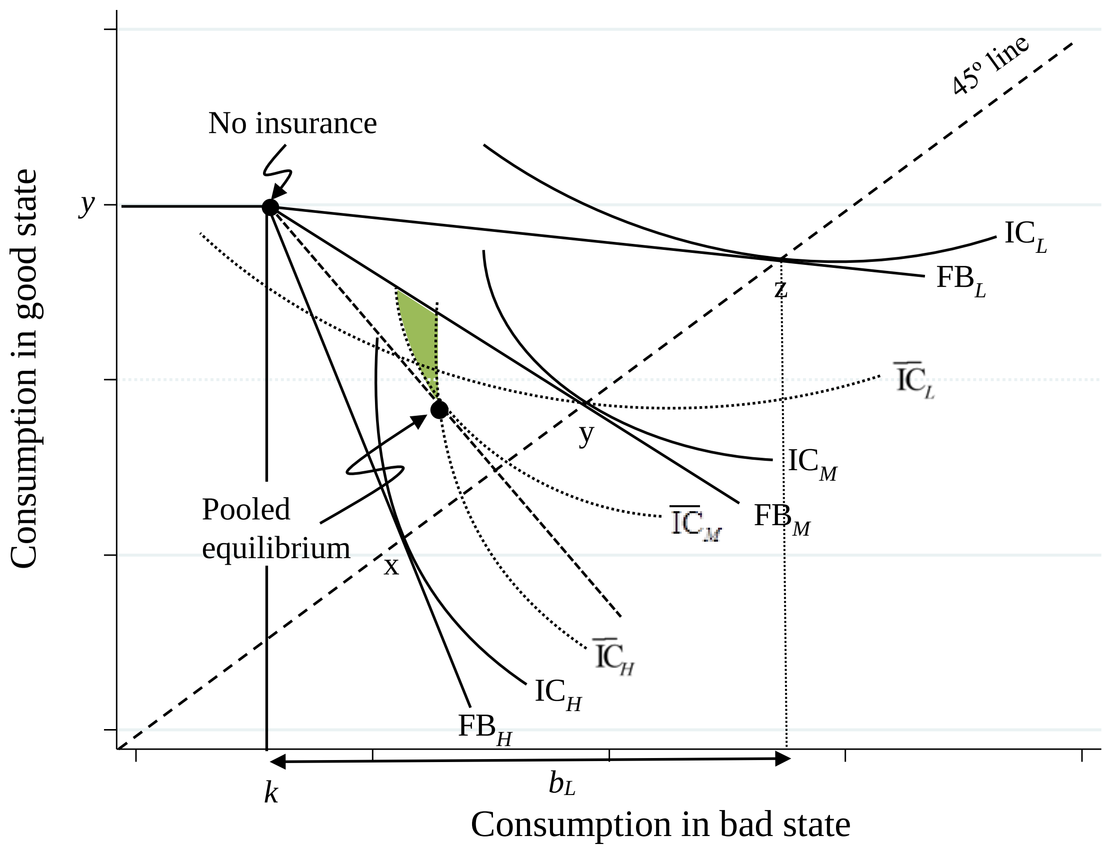
Web appendices

Appendix A: Graphical representatio of the pooled equilibrium with private information and adverse selection

In Figure A5 there are three risk groups, *L*, *M*, and *H*. With no insurance, income is *y* in the good state and *k* in the bad (which are assumed here to be the same for all groups). The solid downward-sloping "fair-bet" (FB) lines are the feasible sets of allocations of income between the two states that would have the same expected value (in the model, the slopes of these lines are $-(1-p_i)/p_i$). Each risk groups would want to allocate enough income for insurance to equalize income in the two states, which are where the fair-bet lines intersect the 45-degree line and the indifference curves (IC) are tangent to each FB line. If risk was common knowledge, and insurance markets competitive, each group would be offered a contract corresponding to these points, denoted x, y, and z in the figure (assuming no costs of provision and zero profits). The benefit, *b*, stipulated in each contract is the difference between income in the good and bad state, which is $b_i = \frac{\pi_i \cdot y_i \cdot (1-p_i)}{p_i}$ in our model (illustrated here along the x-axis in the case of *L*).

Yet, insurers cannot observe the risks of different groups, and they instead have to pool these so that the expected combined payouts are equal to total insurance payments. When risks are pooled across all three groups, the lines are drawn so that this expected payout (contract) line is equal to *M*'s fair-bet line. Imagine now that the insurer offered y as an insurance plan. If all bought the plan the insurer would break even (the zero-profit condition would hold) and the outcome would be sustainable from the perspective of insurers. But it is easy to see that *L* would not buy this plan since *L*'s indifference curve is below the "no insurance" point: *L* would be worse off with insurance than without. With *L* opting out there is a new pooled fair-bet/contract line between *M* and *H*, which is the downward-sloping dashed line. A pooled equilibrium is now feasible since any point on that line (above the 45-degree line) is superior to the no insurance point for both *M* and *H*.

Figure A5: Example of a pooled equilibrium with three risk groups



Note that there is a shaded area above the pooled equilibrium point where *M* would be better off (while *H* would be worse off). In the Rothschild-Stiglitz model a competitive firm could move into this space and make a profit by selling to *M* (the lower risk group) only. That would undermine the pooled equilibrium. But this assumes that insurance companies can monitor the quantity of insurance bought by different groups since otherwise they might end up selling to a high-risk type for a loss. In this example *H* would buy the cheaper plan up to the permitted limit, and supplement with the high-cost plan to get fully insured. If insurers cannot observe purchases, or if they cannot distinguish between low-risk types with high risk-aversion and high-risk types with low risk-aversion, they would not want to move away from the pooled plan and the pooled equilibrium is feasible (although inefficient). This would also be true if insurers can observe purchases and risk-aversion but are able to "collude" to not move away from the pooling outcome. Regulators should in principle not object to such agreements since they preserve the market at a competitive price. In our model pooling equilibria are allowed for one or all these reasons.

Finally, the pooled equilibrium is represented as a single point on the contract line, whereas in the model we have allowed different points on the line in proportion to how much people pay into the system. In that case, the point in Figure A5 represents an average.

Appendix B: Satisfying the insurer's balanced budget constraint

Assuming zero profits the total insurance payout is the area under the cost function from 1 to the critical threshold (the insurance pool) given by eq. (6):

$$\int_{\frac{s}{\frac{1}{\overline{p}}-1+s}}^{1} (p_i \cdot b_i)\, dp = \int_{\frac{s}{\frac{1}{\overline{p}}-1+s}}^{1} \left(p_i \cdot \pi_i \cdot y_i \frac{(1-\overline{p})}{\overline{p}} \right) dp$$

The total insurance revenue is the corresponding area under the revenue function:

$$\int_{\frac{s}{\frac{1}{\overline{p}}-1+s}}^{1} \left((1-p_i) \cdot y_i \cdot \pi_i \right) dp$$

The difference between revenues and costs is profits (which we assume to be 0):

$$\text{Profits} = \text{revenues} - \text{costs} = \int_{\frac{s}{\frac{1}{\overline{p}}-1+s}}^{1} \left(\left[(1-p_i) \cdot y_i \cdot \pi_i \right] - \left[p_i \cdot \pi_i \cdot y_i \frac{(1-\overline{p})}{\overline{p}} \right] \right) dp$$

To assess whether the zero-profit condition holds in equilibrium we need to choose a particular distribution of risks. If this distribution is uniform, as in Figure 3, the amount paid out as insurance in equilibrium is the number of insured, *N*, times the average payout, which is equal to the mean risk times the mean replacement rate: $N \cdot \overline{p} \cdot \overline{y} \cdot \frac{(1-\overline{p})}{\overline{p}}$; and the amount paid into the insurance is the number of insured, *N*, times the average insurance premium: $N \cdot (1-\overline{p}) \cdot \overline{y}$:

$$\text{Profits = revenues - costs = } \left[N \cdot (1-\overline{p}) \cdot y\right] - \left[N \cdot \overline{p} \cdot \overline{y} \cdot \frac{(1-\overline{p})}{\overline{p}}\right]$$

$$= \left[N \cdot (1-\overline{p}) \cdot \overline{y}\right] - \left[N \cdot \overline{y} \cdot (1-\overline{p})\right]$$

$$= 0$$

The insurer's budget is thus balanced in equilibrium. Any point in Figure 3 to the left of the equilibrium and above the 45-degree line means that the insurer expects more payers than people actually taking up the plan. Costs are therefore greater than revenues and the insurer will have to raise the price until the equilibrium is reached.

Appendix C: Information and attitude polarization

Data

This analysis is primarily based on the General Social Survey (GSS) 1972-2014 cumulative file. See gss.norc.org.

Details on the subjective risk survey item

Question wording: “Thinking about the next 12 months, how likely do you think it is that you will lose your job or be laid off – very likely, fairly likely, not too likely, or not at all likely?” (Answer categories [reversed]: 1 Not likely, 2 Not too likely, 3 Fairly likely, 4 Very likely).

This is variable “joblose” in the GSS 1972-2014 cumulative file, available for the following years: 1977, 1978, 1982, 1983, 1985, 1986, 1988, 1989, 1990, 1991, 1993, 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, and 2014.

Details on occupational variables

We use the following occupational variables in the GSS:

- occ [Rs census occupation code (1970)]: 1972-1987
- occ80 [Rs census occupation code (1980)]: 1988-2010
- occ10 [Rs census occupation code (2010)]: 2012-2014

To standardize these different occupational classifications over time, we exploit the fact that the Current Population Survey (CPS) not only codes occupations into the relevant SOC classification for a given year (SOC1970, SOC1980, etc.) but also into SOC1990 for all years. This allows us to use the CPS data to back out a concordance between the SOC-classifications for various years and SOC1990. We use these concordances to code the GSS occupational data into SOC1990.

We use Current Population Survey (Flood et al. 2015) data to derive occupational unemployment rates (OURs) for each year, coded in the same SOC1990 classification, and merge them into the GSS, based on respondents' occupation. To make sure that results are not influenced by outliers, we top-code OURs at 25% (roughly p99).

<u>Attitudes toward unemployment insurance policies</u>

We proxy attitudes toward unemployment insurance policies with the following survey item: "I'd like to talk with you about issues some people tell us are important. Please look at [this card]. Some people think that the government in Washington should do everything possible to improve the standard of living of all poor Americans; they are at Point 1 on this card. Other people think it is not the government's responsibility, and that each person should take care of himself; they are at Point 5. [.] Where would you place yourself on this scale, or haven't you have up your mind on this?" [Reversed scale: 5 Govt. action; 3 Agree with both; 1 People help selves]

This is variable "helppoor" in the GSS 1972-2014 cumulative file, available for the following years: 1975, 1983, 1984, 1986, 1987, 1988, 1989, 1990, 1991, 1993, 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, and 2014.

The GSS contains two survey items that capture attitudes toward unemployment insurance more directly:

- survey item ‘aidunemp’ (“On the whole, do you think it should or should not be the government's responsibility to F. Provide a decent standard of living for the unemployed”)
- survey item ‘jobsall’ (“On the whole, do you think it should or should not be the government's responsibility to A. Provide a job for everyone who wants one”).

These items overlap with the ‘helppoor’ item we use in the analysis for the years 1989, 1990, 1996 (‘aidunemp’) and 1989, 1990, 1991, 1996, 1998 (‘jobsall’), respectively, and they correlate with that item at 0.3147 and 0.3347 (statistically significant at $p<0.01$).

Appendix D: Information and life insurance penetration

Life insurance penetration data

The data are available at https://stats.oecd.org/Index.aspx?DataSetCode=INSIND (OECD insurance indicators). See also OECD (2015b).

Sample: AUS (1984-2013), AUT (1987-2013), BEL (1983-2013), CAN (1984-2013), CHE (1983-2013), DEU (1987-2013), DNK (1983-2013), ESP (1983-2013), FIN (1983-2013), FRA (1983-2013), GBR (1996-2013), GRC (1992-2013), IRL (1983-2013), ISL (1983-2013), ITA (1983-2013), JPN (1983-2013), NLD (1995-2013), NOR (1983-2013), NZL (1989-2003), PRT (1983-2013), SWE (1983-2013), USA (1983-2013).

Mortality by cause data

Our measure of information is based on data about premature mortality, as provided by the OECD (https://stats.oecd.org/index.aspx?DataSetCode=HEALTH_STAT). The original data source is the WHO data Mortality Database (http://www.who.int/healthinfo/mortality_data/en/).

We make use of the "Potential Years of Life Lost" (PYLL) variable, defined in the following way: "This indicator is a summary measure of premature mortality, providing an explicit way of weighting deaths occurring at younger ages, which may be preventable. The calculation of Potential Years of Life Lost (PYLL) involves summing up deaths occurring at each age and multiplying this with the number of remaining years to live up to a selected age limit (age 70 is used in OECD Health Statistics). In order to assure cross-country and trend comparison, the PYLL are standardized, for each country and each year. The total OECD population in 2010 is taken as the reference population for age standardization. This indicator is presented as a total and per gender. It is measured in years lost per 100 000 inhabitants (men and women) aged 0-69." [Source: OECD (2015), Potential years of life lost (indicator). doi: 10.1787/193a2829-en (Accessed on 01 September 2015)].

We calculate potential years of life lost (PYLL) due to the following diseases:

- Certain infectious and parasitic diseases
- Neoplasms
- Diseases of the blood and blood-forming organs
- Endocrine, nutritional and metabolic diseases
- Mental and behavioural disorders
- Diseases of the nervous system
- Diseases of the circulatory system
- Diseases of the respiratory system
- Diseases of the digestive system
- Diseases of the skin and subcutaneous tissue
- Diseases of the musculoskeletal system and connective tissue
- Diseases of the genitourinary system
- Certain conditions originating in the perinatal period;
- Congenital malformations and chromosomal abnormalities.

These diseases account for about 75% of PYLL – the remaining PYLL are largely due to "external causes of mortality" (traffic accidents, accidental poisoning, suicides, etc.).

The WHO data rely on the International Statistical Classification of Diseases and Related Health Problems (ICD). Over time, the ICD has been updated. In the empirical analyses, we include an indicator variable for changes the ICD-classification. The potential breaks occur in the following country-years: Australia (AUS): 1968, 1979, 1998. Austria (AUT): 1969, 1980, 2002. Belgium (BEL): 1968, 1979, 1998. Canada (CAN): 1969, 1979, 2000. Denmark (DNK): 1969, 1994. Finland (FIN): 1969, 1987, 1996. France (FRA): 1968, 1979, 2000. Germany (DEU): 1998. Greece (GRC): 1968, 1979. Iceland (ISL): 1971, 1981, 1996. Ireland (IRL): 1968, 1979, 2007. Italy (ITA): 1968, 1979, 2003. Japan (JPN): 1968, 1979, 1995. Luxembourg (LUX): 1971, 1979, 1998. Netherlands (NLD): 1969, 1979, 1996. New Zealand (NZL): 1968, 1979, 2000. Norway (NOR): 1969, 1986, 1996. Portugal (PRT): 1971, 1980, 2002. Spain (ESP): 1968, 1980, 1999. Sweden (SWE): 1969, 1987, 1997. Switzerland (CHE): 1969, 1995. United Kingdom (GBR): 1968, 1979, 2001. United States (USA): 1968, 1979, 1999.

<u>Partisanship variable and controls</u>

Since partisanship only has an effect through slow-moving regulatory measures, we use Huber and Stephens' (2001) cumulative measure of left seats in government (divided by the number of years), starting in 1960. This measure does not change much in our sample, and since we estimate fixed effects models, it is not clear that estimating direct effects of partisanship is meaningful. We report results for including left partisanship both as an independent variable and as an interaction with information, but our focus is on whether left partisanship slows the progression of markets in response to information, as hypothesized above.

Finally, we include three control variables that may influence life insurance penetration: (i) the percentage of the population covered by public or primary private health insurance; (ii) total health expenditure (all financing agents) as a % of GDP; and (iii) the rate of economic growth.

Sample

The following country-years are in our sample, which is determined by data availability: AUS (1985-2011), AUT (1988-2013), BEL (1984-2012), CAN (1985-2011), CHE (1984-2012), DEU (1993-2013), DNK (1984-2012), ESP (2011-2011), FIN (1984-2013), FRA (1991-2011), GBR (1997-2013), GRC (1993-2008), IRL (1984-2010), ISL (1984-2009), ITA (1989-2012), JPN (1984-2012), NLD (1996-2013), NOR (1984-2013), NZL (1990-2001), PRT (1984-2013), SWE (1986-2013), USA (1984-2010).

Results

The estimation results are shown in Table D1. The only difference between the models in D1 is whether and how cumulative partisanship is entered as an explanatory variable. Model (1) does not contain a partisanship variable, while Model (2) does – both as an independent variable and as an interaction with information. Finally, Model (3) only includes partisanship only as an interaction term. Because the cumulative partisanship variable does not move much within countries over time it carries little information not already contained in the fixed effects. The interaction, on the other hand, tests whether the effects of changes in information are conditioned by stable differences in partisanship, the key question for our partisan hypothesis.

The controls are health insurance coverage (% of population); total health expenditures (% of GDP); economic growth rate; partisanship; country dummies; and an indicator variable for potential breaks in the PYLL series. The coefficient on PYLL is 1.032 with a SE of 0.036; adj. R2=0.887, F-value=180. Because the resulting variable is estimated, we adjust the variance-covariance matrix in the reported results by applying the correct mean squared error (Baltagi 2011).

Table D1: Life insurance penetration, information, and partisanship (OLS and ECM)

	(1)	**(2)**	**(3)**
	Dependent variable: Life insurance penetration [first difference]		
Life insurance penetration [lag]	-0.183* (0.071)	-0.219** (0.075)	-0.203** (0.073)
Information [lag]	1.451* (0.672)	3.273** (1.154)	2.838* (1.105)
Information [first difference]	3.040+ (1.765)	2.800 (3.842)	1.679 (4.239)
Left partisanship X Information [lag]		-0.034** (0.013)	-0.033* (0.014)
Left partisanship X Information [first difference]		0.023 (0.084)	0.054 (0.089)
Left partisanship		0.021* (0.010)	
Health insurance coverage (% of population)	-0.018 (0.028)	-0.028 (0.029)	-0.024 (0.031)
Total health expenditures (% of GDP)	-0.133 (0.097)	-0.139 (0.094)	-0.150 (0.102)
Economic growth rate	0.049* (0.024)	0.050* (0.024)	0.053* (0.025)
Constant	3.122 (2.956)	3.385 (2.954)	3.911 (3.252)
Dummy for breaks in PYLL-series	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
N	486	486	486
N of countries	22	22	22
Adj. R2	0.124	0.144	0.138

Note: Coefficients above SEs. + p<0.10, * p<0.05, ** p<0.01

The results for information across all three models are very similar: the lagged dependent variable is statistically significant, with an estimated coefficient of around -0.2, and the lagged information variable is positive and statistically significant (indicating that more information is associated with higher life insurance penetration). The coefficients on the regressors have very specific interpretations: the coefficients on the lagged level variables capture permanent effects of a one-off change in those variables, while the coefficients on change variables capture transitory effects (Beck and Katz 1995). We find that there are short-term transitory effects (not statistically significant), but that the main effects are long-term and permanent.