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Risk-taking, skill diversity, and the quality of human capital: how insurance affects innovation

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Abstract

We argue that human capital does a better job of fostering innovation when an economy has a diverse portfolio of specialist skills to draw on. While such a diverse portfolio is beneficial for a country, it includes many individual skill packages that are subject to considerable labour market risk. In the absence of strong income insurance (job security or unemployment insurance), the flight to safety in human capital investments will produce a national skill portfolio which is poorly diversified and less conducive to innovation.

Using country-level data for 25 OECD countries from 1985 to 2009, we find evidence that income insurance raises the marginal effect of human capital on innovation, with the latter measured by patenting. At the same time, we find a direct negative effect of insurance on patenting; at low-medium levels of human capital, the direct negative effect more than offsets the positive indirect effect, while at high levels of human capital the indirect positive effect dominates. We draw implications for income insurance and education policy.

Keywords: innovation, skills, human capital, evolutionary economics, flexicurity

JEL code: J24; O31.

1 Introduction

Human capital fosters innovation. This is not simply because human capital as an input to production complements capital or more advanced technologies, but because well educated workers are better at developing and adopting new methods, and indeed at learning new things (Nelson and Phelps 1966, Vona and Consoli 2015, Consoli and Rentocchini 2015).

But what *kind* of human capital contributes most to innovation? We argue that, other things equal, innovation is fostered by a diverse social portfolio of skills. This follows from the logic of evolutionary models of the economy and of innovation: a system characterized by great variety should be more effective in responding to economic and technical change by continuous innovation, by means of finding and selecting the more efficient adaptive and 'creative response' (Schumpeter 1947, Alchian 1950). In order to be competitive firms need to have knowledge in excess of what they need for what they make to cope with technological development: firms need to "know more than they make" (Brusoni, Prencipe and Pavitt 2001). If successful innovations are those selected from a variety of experimental attempts, strategies and solutions to economic problems, then a diverse national portfolio of skills should be conducive to innovation (Nelson and Winter 2002).

Whatever the aggregate benefits of a diverse skill portfolio, human capital choices are to a substantial extent made by individuals, and for individuals human capital can be a risky investment. A particular course of study may produce a skill set for which demand vanishes at some unknown point in the future – it may vanish because of technological change, offshoring, or the fortunes of an individual's career. Because of this uncertainty, an individual's educational choices will be affected by insurance. That insurance might come in the form of family financial resources (Saks and Shore 2005), unemployment insurance, which shifts the burden of adjustment to the state (Krebs 2003), job security, which shifts the burden to the employer, or some combination of unemployment insurance and job security (Estevez-Abe, Iversen and Soskice 2001, Filippetti and Guy 2015): an umbrella label for these is "income insurance". Where all forms of income insurance are weak, individuals will tend to choose safer options – skills which are either more general or which pertain to occupations thought to be secure. In the aggregate, this flight to safety can be expected to produce a national skill portfolio that is poorly diversified, and relatively deficient in specialized skills. By contrast, the presence of insurance will encourage a more diversified structure of specialized skills in the economy.

Previous studies have used standard measures of human capital, based on years of schooling, levels of qualification attained, or rates of literacy and numeracy, to study the impact of skills on innovation (Evangelista and Savona 2003, Tether et al. 2005, Toner 2011). We are instead concerned about developing and testing the following argument: as income insurance grows stronger, the *marginal* effect of human capital on innovation should also rise.

The effect of income insurance on a national human capital portfolio will not be seen in standard measures of human capital, based on years of schooling, levels of qualification attained, or rates of literacy and numeracy. It should, however, be seen in the effect which human capital has on innovation: as income insurance grows stronger, the marginal effect of human capital on innovation should also rise.

We test this hypothesis on a panel of data for OECD 25 countries between 1985 and 2009. We find that the marginal contribution of human capital to national rates of patenting does rise as income insurance grows stronger. We draw implications for employment protection, flexible security ("flexi-curity"), and industrial policy.

In the Section 2.1 of this paper, we consider first the relationship between educational choices, skill, risk, and insurance; in 2.2, we distinguish between specificity of skill (firm-specific, industry-specific, etc), and the related but distinct issue of uncertainty of demand for the skill; in 2.3, we review previous findings on how different types of skill affect innovation; in 2.4, we review previous findings on types of skill in the knowledge economy; in 2.5, findings on types of skill in national systems of innovation; and in 2.6, findings on direct effects on income insurance on innovation. Section 3 describes our data; Section 4.1 explains our model, and our estimation results are presented in Section 4.2. Section 5 concludes, discussing implications and avenues for future research.

2 Background

2.1 Educational investment and risk

Educational choices are risky investments for the individual. Risk can affect both the amount of education an individual undertakes, and what the individual chooses to study if and when they do study. Ellwood and Kane (2000) find that prospective students react more strongly to costs of tertiary education than to expected returns. Carneiro, Hansen and Heckman (2002) explain Ellwood and Kane's finding as being, in part, the result of a combination of these factors: most of the variance in returns to college (university) cannot be forecast at the time the college attendance decision is made; individual or family financial constraints; and risk aversion. Saks and Shore (2005) show that students from families with greater financial resources undertake courses of study which are riskier, in the sense of having higher variance in returns to education. Krebs (2003) does not distinguish between types of human capital, but shows that the typical risk in human capital investment in the USA depresses this investment and raises investment in less productive physical capital; he shows that government severance payments to displaced workers (a form of income insurance) should more than pay for themselves.

2.2 Skill specificity and skill risk

In the classic treatment of investment in human capital, risk is not a problem. Becker (1962) distinguishes between firm-specific and general skills, and claims that investment in firm-specific skills is paid by employers, investment in general skills by workers. Some of the literature, following this, treats "specific" as synonymous with "firm-specific". We, however, are concerned primarily with skills which are specific to an industry, occupation, or use of a particular technology. Such skills are general from the standpoint of the employer (because the employee, once trained, may move to a different employer), yet specific from the standpoint of the worker (because the skill loses value if the worker seeks work in a different industry or occupation, or if the technology becomes obsolete).

For the worker, investing in specific skills may pose a substantial risk. It is useful here to think in terms of cases in which demand for a set of skills may decline abruptly in mid-career. The decline might be due to changes in national specialization in the international trading system, or to the obsolescence of the technologies associated with the skills: hence, many sewing machine operators, computer programmers, radiologists and others have woken up one day to find that demand for their skills has been offshored, while a generation ago underground coal miners, typesetters and mainframe computer operators found themselves replaced as new technologies and new methods were adopted. The same reasoning can also be applied to skills for any job in which the career advancement is highly uncertain - for instance, in arts and in professional sports, where only a small proportion of those who train are even able to make a living, while a small handful make substantial fortunes.

Not all specific skills are risky investments for workers, however. There are skills which are specific but relatively safe: skills for most medical and nursing specialisms, teaching, hairdressing, and plumbing, to name but a few. The skills required for such occupations seem, on past form, to be neither readily off-shorable nor subject to abrupt technological displacement.[1] For the worker, specific skills of this sort may be as safe an investment as any general (widely transferable) skill. For this reason, we distinguish not between general and specific skills, but between skills which represent safe investments for an individual worker, and skills which represent risky investments. Risky skills are a subset of specific skills.

2.3 Vocational skills as specific, and risky

Vocational education and training (VET) is often regarded as providing skills which are more industry- or occupation-specific, compared with academic education which provides skills which are more general. Because of this, VET-acquired skills are said to entail greater labour market risk. Lamo et al (2011) find that Polish and Estonian workers with VET qualifications have higher unemployment rates than those with university qualifications, a fact which they attribute to the greater specificity of the former – the risk of unemployment is evidently greater for those with VET qualifications. Hanushek et al. (forthcoming), using micro data for eleven countries, find that workers with vocational qualifications are more employable immediately after completing their education, but have higher unemployment rates later in life.

[1] We are of course conscious of the risk of hubris on this point – who among us is not, ultimately, vulnerable to replacement by a robot? – but the salient question is not whether our statement about such occupations will continue to hold true, but whether it is believed to be true by people making educational choices in preparation for a career.

Estevez Abe et al (2001) share the view that VET is a relatively risky human capital investment, and attribute differences in national levels of enrolment in VET to differences in income insurance: countries with high levels of employment protection (EP) and/or with unemployment benefits ensuring high income replacement rates (RR), have higher rates of enrolment in VET than countries in which both EP and RR are low.

Though demand for VET skills may, on average, be more uncertain than demand for those obtained through academic study, they are not *uniformly* risky. Filippetti and Guy (2015) find that the national VET enrolment has a positive effect on innovation investment by firms when income insurance is sufficiently strong, and has a negative effect if insurance is sufficiently weak; they infer from this that the skills obtained through VET when insurance is strong are different – and more conducive to innovation – than those obtained when insurance is weak.

2.4 Types of skill and the post-mass production economy

The literature on innovation and skill is largely framed with reference to general vs. specific skills, without reference to risk (risk-taking on the part of the entrepreneur is, of course, often considered a driver of innovation; that on the part of the worker, not so much.) For the reasons we have given above, we are interested in the riskiness of the human capital investment – uncertainty of labour market demand for a specific skill – rather than specificity *per se*. Yet, for the most part, risky skills are a subset of specific skills, and the firm-, industry- occupation- or technology-specific skills which figure in discussions of skill and innovation tend also to be risky ones. We need to consider, then, how the link between innovation, and specificity or generality of skill, has been understood.

There are two broad ways into this question. One is over time: what kinds of skill serve the individual best in today's economy, which is understood as a knowledge economy and as requiring or rewarding different skill sets than previous economies. The other is across innovation systems, and in particular national innovation systems, which may be understood as favouring different kinds of skill.

Today's economy is often seen as requiring more general skills, in comparison with the manufacturing-dominated economy of the mid-twentieth century, which is said to have rewarded more specific ones. Gould (2002) finds, in the US labour market between 1970 and 1990, that demand has shifted away from specific and toward general skills, producing greater mobility between industries and occupations. It is possible that the shift towards general skills in the US, demonstrated by Gould, and the bad employment outcomes for those with VET educations in Poland and Estonia, shown by Lamo et al. (2011), result not from technological change but from the removal of EP: the decay of internal labour markets in the US case (Doeringer and Piore 1971, Osterman 1996), and the removal of statutory job security in post-communist Poland and Estonia. Krueger and Kumar (2004a, 2004b), however, make the case that the skills obtained through VET make it costly for employers to adopt modern information-based technologies, and so have become a barrier to innovation; in this way they explain the shift in advantage in productivity growth from VET-heavy Europe in the 1960s and 70s, to the university-heavy US in the 80s and 90s. In Krueger and Kumar's view, different national skill sets are due to differences in educational policy; however, if they are correct that specific skills are less suitable to the information age, it would not matter if the source of these differences in national skill sets was education policy, or the incentive structure provided by income insurance per Estevez-Abe et al.

2.5 Types of skill, insurance, and national systems of innovation

Gould (2002), and Krueger and Kumar (2004a, 2004b), associate specific skills and general skills with two different technological eras. An alternative interpretation associates them with distinct, but contemporaneous, national systems of innovation. Systems of innovation rooted in national institutions (e.g. Lundvall et al. 2002, Fagerberg and Sapprasert 2011) are often described with particular reference to the interface of industry with advanced science and technology, and the associated high-level skills. However, one particular typology of national innovation systems, that of Hall and Soskice (2001), requires comment, for three reasons: one is that the question of specific vs. general skills of the broad workforce plays a key role in their typology; the second is that income insurance – EP and RR – is at the center of their explanation for why national specialization in specific or general skill is maintained; the third is that, despite these commonalities, we do not follow Hall and Soskice in the use of the distinction between radical and incremental innovation.

The two types of national system of interest to Hall and Soskice are what they call "coordinated market economies" (CMEs) and "liberal market economies" (LMEs). In the former, innovation tends to be incremental, heavy use is made of specific skills, and at least one form of income insurance – EP, RR, or both – is strong. For the latter, the comparative advantage is in the products of radical innovation; radical innovation is said to match with general skills, because in its disruptive and uncertain nature radical innovation benefits from the ability to quickly mobilize, and de-mobilize, workers, to hire and to fire — which is to say, with very weak EP (the role of weak RR is less clear, though it is the rule in almost all of their LMEs). In their analysis, CMEs are typified by Germany, LMEs by the United States.

Herrman and Peine (2011), studying pharmaceutical firms in Germany, Italy, and the UK, do find that firms employ scientists with general knowledge when pursuing radical product innovation, and scientists and other employees with more specific knowledge when pursuing strategies of incremental innovation or simple imitation. Yet this does not support Hall and Soskice’s more contentious claim that the national economies of the leading OECD countries tend either to ‘radical’ or to ‘incremental’ innovation on the basis of the training of their workforces. A wealth of long-established research (e.g. Freeman and Perez 1988, Rosenberg 1976, Rosenberg 1982) has found that in order to be effective, radical innovations need a long process of incremental improvement and diffusion, which makes them two parts of the same process, often (though not necessarily) occurring within the same country. In this vein, Meisenzahl and Mokyr (2011) provide evidence that the critical knowledge component of the first industrial revolution — a setting of radical innovation if ever there was one — lay not in Britain’s vaunted scientific leadership, but in apprenticeships.

It is therefore not altogether surprising that the radical-vs-incremental element of the Hall-Soskice characterization of national systems, has not fared well in empirical tests. Taylor (2004) finds that any difference in the prevalence of radical innovation between countries classified as CMEs and those classified as LMEs by Hall and Soskice is explained by one single LME – the USA – with the other CMEs and LMEs essentially indistinguishable; Taylor uses patent data, and assesses the radicalness of an innovation by the count of forward citations in other patents. Akkermans et al (2009) use the same data but different measures of radicalness (Hirschman-Herfindahl type indices of the dispersion of both forward and backward citations across industries); their result for forward citations (measuring the cross-industry dispersion of a patent’s influence) is similar to Taylor’s, while that for backward citations (measuring a patent’s originality through the cross-industry dispersion of the sources cited in the patent) is somewhat stronger on average in LMEs than in CMEs. In both cases they find considerable heterogeneity within the LME and CME groupings, and an outlier position for the United States. The most salient outcome of both studies is that the US is an outlier in the production of radical innovations; this cannot be explained by what we know of human capital differences, or by differences in income insurance or other labour market institutions. There are other ready explanations for this, notably the guiding role of the state, and in particular, the military (Block and Keller 2010, Ruttan 2006, Mazzucato 2011), which depart from the Hall-Soskice framework and which are also beyond the scope of the present study.

Schneider and Paunescu (2012) have come to the defense of Hall and Soskice's radical/incremental distinction using, as a measure of radicalness, revealed comparative advantage in industries which the OECD classifies as high technology; and, for incremental, revealed comparative advantage in industries the OECD classifies as medium-high. Their contribution is to refresh the Hall-Soskice institutional typology via the cluster analysis of eight institutional variables; they end up with five types of national system, including CME and LME. Their variables do not include RR or anything comparable, so income insurance works only through EP. This is presumably why, in many years, they classify Denmark Sweden, Switzerland, the Netherlands and Finland as LMEs or "LME-like", while all other analyses have had them as CMEs.

In the present paper, we do not attempt to distinguish between radical and incremental innovation; nor do we classify countries. We do use two income insurance variables – EP and RR - which capture elements important for the Hall-Soskice institutional typology, and even more important for the Estevez-Abe et al. (2001) elaboration of that typology with regard to income insurance and skill formation. Our departure is to think in terms of the effect income insurance may have on risk taking in human capital investments generally: rather than seeing it as something which affects the shares of the population choosing vocational or academic education, we see within any *type* of education a spectrum of risk-taking possibilities, chances to either play it safe by becoming generalists or double down by acquiring deeper specialized knowledge in some particular area. Such choices are faced in different forms by people studying arts or sciences just as much as by people studying for particular vocational qualifications. This risk-taking (or rather, the pooling of individual risks through the insurance system) generates a greater variety of skill and expertise; variety, in the perspective of evolutionary economics, is a key aspect of innovation since it increases the number and, more importantly, the spectrum of strategies and action attempted by firms (Dosi 1988, Boschma 2005). In this view innovation is conceived as a discovery process in which "*what really counts is the various actions actually tried, for it is from these that success is selected, not from some set of perfect actions*." (Alchian 1950, 220). Within economic systems which change as a result of firms continuously adapting their production processes though adjustments based on ongoing experimentation and trial-and-error learning (Nelson and Nelson 2002), we argue that a more diversified portfolio of specialized skills leads over time to higher aggregate innovation performance.

2.6 EP and RR: different effects?

Thus far we have considered the effect EP and RR may have on human capital choices, and the effect this may have on innovation. We have treated the two forms of insurance as equivalent, and have considered only this indirect effect.

Several researchers have studied the direct effect of EP on innovation. Barbosa and Faria (2011) find that EP reduces the likelihood that firms in different European countries will be classified as innovators in the Community Innovation Survey. Griffith and Macartney (2013) study patenting by multinational firms at different locations in Europe, and get mixed results, with a raw count of patents positively associated with EP, but a count weighted by the patents' citations of scientific journals negatively associated with EP. Acharya et al. (2012), comparing patenting in different US states over time, find a positive association with the strength of EP in the form of wrongful discharge laws. In short, the evidence on the direct effect of EP on innovation is mixed and inconclusive.

EP could have a deleterious effect on innovation simply through the allocation of existing human capital, rather than by affecting the quality: limited inter-firm mobility of workers may impede the matching of existing skills with new innovation opportunities. The same logic does not apply to RR which, if anything, encourages the separation of poorly matched workers from their employers.

The indirect effect of EP on innovation – via skill formation – has featured in a comparative institutional literature that is the forerunner of the Hall-Soskice framework. This literature sees EP as contributing to incremental innovation. In Japan, (non-statutory) employment protection combined with anti-poaching collusion between employers is seen as sustaining high employer investment in skills (often assumed, in keeping with the standard human capital model, to be firm specific), while in fact the lack of employee mobility also facilitates training in skills that could otherwise be taken to a competitor (Aoki 1988). In Germany and countries with similar institutions (notably Austria, Switzerland, part of Belgium and certain regions of Italy), cost sharing among employers is seen as overcoming problems of free riding on training for industry-specific skills (Culpepper 2001). See also Hollingsworth and Boyer (1997), Streeck and Yamamura (2001), and Thelen (2004). In general, this argument runs that a high cost of dismissing workers provides an incentive for firms to retrain them, and to find new (innovative) uses for them (Lucidi and Kleinknecht 2010); this treats workers who are costly to dismiss as attracting a quasi-rent, in a way analogous to Penrose's (1959) theory of a firm's organizational capability for growth.

In recent years, interest has shifted to the possible contribution of RR to skills and innovation, often as part of a package labelled 'flexicurity' or 'flexible security' (Commision of the European Communities 2007, Council of Europe 2005). Flexicurity takes different forms in different times and places, and the use of the term itself is perhaps too flexible in policy documents (Viebrock and Clasen 2009); we mean something like the Danish mix of weak EP; high but time-limited term RR; and retraining which can be provided prior to re-employment, through a strong state-sponsored vocational education and training (VET) system.

Holm et al (2010) provide evidence that flexible security promotes innovation, and that the skills they say flexible security engenders in the workforce are one important reason for this. Moreover, they find that in addition to skills brought to the job (from VET and elsewhere), workers in countries that score highly on their flexible security measure actually engage in more discretionary learning while employed than do workers in other countries in Europe.

In the flexicurity literature, the issue of skill specificity is not often addressed, although it is implicit in the RR-plus-retraining policy package.

2.7 Implications and hypotheses

Our hypothesis concerns the indirect effect of income insurance on innovation, via its effect on the composition of human capital:

> *H.1 Strong insurance engenders a diverse national portfolio of specific skills, and will strengthen the marginal effect of measured human capital on innovation.*

An alternate hypothesis combines the proposition that social insurance encourages investment in specific skills, with the Krueger and Kumar (2004a, 2004b) finding that specific skills are a barrier to innovation in the contemporary economy, we have a contending hypothesis of a negative relationship:

> *H.2 Because social insurance encourages more specific skills, stronger social insurance will weaken the marginal effect of measured human capital on innovation.*

Variants of these two hypotheses would apply them only to EP, or to RR.

Finally, we must consider that either EP or RR may have a direct effect, either positive or negative, on innovation.

3. Data

Our data are all at country level, for 25 OECD countries between 1985 and 2009. We have all 25 countries from 1993; from 1985 to 1992 we are missing six: New Zealand, plus five central European countries from the old Soviet bloc. The countries and number of years each is in the dataset shown in Appendix 1, Table A.2.

Our measure of innovation is international Patent Cooperation Treaty patents per capita (PATENTS). Statistics on patents are among the most frequently used measures in innovation research because of the good availability and reliability of long time-series, and their comparability across countries. It should be noted, however, that not all innovations are associated with patents, and not all patents lead to new products or processes. Moreover, the usefulness of patents as a measure of innovation varies greatly across industries (Fontana et al. 2013). Nonetheless, patents have been widely used in accounting for technological innovation developed for commercial purpose (Griliches 1990), and the literature treats it as a “tolerable assumption” that they measure commercially useful innovation (Schmookler 1962, Archibugi 1992).

There are three main types of patent statistics: patents filed with individual countries' patent offices; international patent applications, also referred to as Patent Cooperation Treaty (PCT) applications; and triadic patent families. Both PCT applications and triadic patents tend to be preferred over the use of data on the first type – i.e. data on patents filed with different patent offices – for two main reasons. Firstly, data published by different patent offices are not necessarily comparable across countries, or even within countries over time, due to differences in legal and administrative practices as well as changes in government policies. For example, in China part of the recent patent surge can be explained through increasingly pro-patent policies (Hu and Jefferson 2009). Secondly, there is a home bias in the filing of domestic applications - more patents are filed by residents of a country compared with non-residents (OECD, 2009). For these reasons we shall here use data from PCT. We prefer them to triadic patent applications because the latter tend to be rarer especially for less advanced countries.

PCT applications are patent applications filed with a patent office under the Patent Cooperation Treaty. A PCT application provides the option to file the same patent with the national office of the member states at a later stage (within 30 months).[2] In our dataset, the reference country for PCT applications is the inventor's country of residence.

Our measure of human capital (HC) is the Barro-Lee (2010) index based on mean years of schooling (average number of years of school completed in population over 14).

Our measure of employment protection (EP) is the OECD Employment Protection Index. This is a measure of the procedures and costs involved in dismissing individuals or groups of workers, and the procedures involved in hiring workers on fixed-term or temporary work agency contracts. For the Replacement Rate (RR), we use Van Vliet et al.'s elaboration of the OECD indicator, since it provides a longer consistent series (Van Vliet, Caminada and Goudswaard 2012). Their measure of replacement rate is the net Unemployment

[2] The filing can be done with a national office or the WIPO, and can be done immediately or within a 12-months priority period from an initial filing of a domestic patent. PCT applications undergo an international search, while domestic patents undergo a national search only.

Replacement Rate for an Average Production Worker, for a single person. We should note, of course, that there is never a single simple "level" of EP or RR within any one country. EP provisions vary within countries across industries and contract types. The OECD index that we use takes into account legal barriers to employee dismissal, but does not factor in the power of unions to provide additional barriers. The level (rate) of RR, and the eligibility for receiving it, both vary *within* countries at any given time, as do EP provisions. This means that EP and RR should be understood as measurements *with error* of the actual insurance provisions.

We control for a number of factors which various studies have indicated as determinants of innovative activity. INFRASTRUCTURE is a measure of telecommunications and electrical infrastructure, which is obtained using the first principal component of the following variables: telecommunication revenue, electric power consumption, internet users, and mobile and fixed-line telephone subscribers. OPENNESS – measured as the share of trade on GDP - can also affect innovation through a number of different channels, e.g. competition, imports, technology transfer and flows of knowledge (e.g. Filippetti and Archibugi 2011). A control for the level of economic development is fixed CAPITAL per capita (e.g. Evangelista 1999); we use this rather than GDP per capita because the latter would be a plausible dependent variable in a similar regression, and is thus a bad control (Angrist and Pischke 2009, 64-68). Finally, we control for an important direct input to innovation and in particular to patenting, which is research and development expenditure per capita (R&D). Variable definitions and sources are summarized in Table 1.

[TABLE 1 ABOUT HERE]

Figure 1 shows plots EP and RR. The three panels in the top row show observations for the 18 countries for which we have data for all 25 years, 1985-2009. The two panels in the bottom row show observations for the seven countries for which we do not have the full series; 1993 is the first year for which data on all of these countries is available. The vertical and horizontal lines in each graph show the overall sample means for the year in question.

For some countries, there are substantial changes in relative position in the EP/RR plots. For example, in 1985 Italy had above-average EP but extremely low RR: that is, job security was strong, but there was virtually no public safety net. By 2009 Italy had come to have a high level of RR, while retaining a high level of EP. By contrast, countries such as Spain have moved from a position of high-ER and high-EP towards the middle of the chart as a result of a reduction of both. There are also cases of countries that have not changed significantly their position, among them Portugal (which remains the most protected labour market in the OECD countries), the Netherlands, France, Denmark and Germany.

The lower left hand corners of the scatterplots – where both EP and RR are relatively low – were occupied in 1985 by three English-speaking countries: Australia, the United Kingdom, and Ireland. In the Hall-Soskice terminology, and on the similar plot in Estevez-Abe et al. (2001, Figure 1), this is the corner in which we should find liberal market economies (LMEs). Notable in its absence from this corner is the USA, which many would see as the archetypal LME; the USA and Canada actually have substantially higher RR than the other LMEs. Notice that in the 1993 sample this low-insurance corner of the plot again includes Australia, the United Kingdom, and Ireland, but now also New Zealand and, close at hand, Poland, neither of which was in the 1985 sample. By 2009, reductions in Poland's RR have moved it further into this zone, and radical cuts in unemployment benefits have moved Hungary there as well.

[FIGURE 1 ABOUT HERE]

For estimation purposes, we winsorize our insurance variables, recoding observations greater than 2.5 s.d. from the mean to the 2.5 value. See Appendix 2 for details.

4. Estimation strategy and results

4.1. Estimation strategy

We begin by allowing EP and RR to have independent and additive effects, both directly and in interaction with HC. Setting aside for the moment the question of the estimator, the model has this general form:

$$PATENTS = \beta_1 * HC + \beta_2 * EP + \beta_3 * RR + \beta_4 * EP * HC + \beta_5 * RR * HC + controls + \upsilon_i + \varepsilon_{it} \qquad (1)$$

Notice that for both EP and RR we include main effects (β_2 and β_3), and also interactions with HC (β_4 and β_5). The main effects are of course the direct effects, which are of some interest, but for our principal hypotheses their role is simply to get valid estimates for the interaction terms. It is the interactions which tell us the association between the insurance variables, human capital, and patenting.

There are limits to what estimates of (1) can tell us about H1 and H2, however, because it treats the effects of EP and RR as independent and additive. If EP and RR are, with respect to educational choice, simply two alternative means of accomplishing the same end, then it is not clear that both would be relevant in any given country and year. For an individual covered by both kinds of insurance, only the stronger of the two should matter: in situations where EP is sufficiently strong, marginal changes in RR should be irrelevant, because the firm continues to employ the worker, who never needs unemployment insurance; conversely, if RR is very strong and EP is weak, marginal differences in EP are not important. If EP and RR apply to the same workers, then under either H1 or H2, observations on EP (or RR) would sometimes be measuring something which has an effect, and other times measuring something with no effect. If this were so then, since equation (1) doesn't distinguish between the observations where EP (or RR) has an effect and ones where it doesn't, under H1 and H2 this specification would create a substantial errors-in-variables problem, biasing the estimates of β_4 and β_5.

For a better test of H1 and H2, we want a single measure of insurance which is the greater of EP and RR in a given country and year. Our measure of this is the greater of our standardized EP and RR variables: MAX(EP,RR), or MAX. MAX is not by any means a perfect measure, since our measures of EP and RR are not directly comparable, so that by saying that one is "larger" than the other introduces a measurement error of its own. RR represents unemployment benefits, net of tax changes, as a percentage of previous income; EP is an index representing the relative institutional barriers to dismissing employees. We believe that use of MAX is justified if we can make the following assumption: both EP and RR have been instituted as functional methods of providing income insurance; their levels (the strength of the insurance) vary depending on the objectives of different national governments at different times, but the range in insurance effect from strongest to weakest is about the same for EP and RR. If this is true (and maintaining the assumption, made in all models here, that the insurance effects are linear), then MAX should be a reasonable approximation of a country's relevant level of income insurance. Furthermore, notice that when differences between EP and RR are small, there is not much difference between using

EP or RR, or MAX; it is only for observations where the difference between EP and RR is large (a country-year where one is very high and one is very low, for instance) that the choice of measures would make much difference in the regressions – and those cases are exactly where MAX should be a better measure than EP and RR, as discussed in Section 2.7. To test these hypotheses, we will estimate a model of this general form:

$$PATENTS = \beta_1 * HC + \beta_2 * MAX + \beta_3 * MAX * HC + controls + \upsilon_i + \varepsilon_{it} \qquad (2)$$

Random effects estimates are produced with Stata's xtpcse command, with panel (i.e., country)-specific Prais-Winsten corrections for serial correlation. The choice of random effects over fixed effects follows Clark and Linzer (2015); see Appendix 2 for details. We run versions of the models both with and without the inclusion of country means for certain controls. The purpose of including the country means is to wash out correlation between the controls and the estimator's individual (country) effect, which can produce random effects coefficients that are too large; there is reason to believe, however, that the procedure may over-correct, for which reason we also report estimates without the country means included. The inclusion of the country means follows Mundlak (1978). In general, the estimates which include country means of the controls should be conservative, and those without these means should be at the higher end (given the limitations of our data, we will not go so far as to call them lower- and upper *bounds*). See Appendix 2 for details. All models also include the controls listed in Table 1, and time (year) dummies.

Table 2 shows Pearson correlation coefficients among the variables in the estimation sample.

[TABLE 2 ABOUT HERE]

4.2. Analysis and Results

We obtain random effects (error components) estimates of the following models:

(0) $PATENTS = \beta_1 * HC + controls + country\ means\ for\ problematic\ controls + \upsilon_i + \varepsilon_{it}$

(1A) $PATENTS = \beta_1 * HC + \beta_2 * EP + \beta_3 * RR + \beta_4 * EP * HC + \beta_5 * RR * HC + controls + country\ means\ for\ problematic\ controls + \upsilon_i + \varepsilon_{it}$

(1B) PATENTS = β_1*HC* + β_2*EP* + β_3*RR* + β_4*EP*HC* + β_5*RR*HC + controls* + $\upsilon_i + \varepsilon_{it}$

(2A) PATENTS = β_1*HC* + β_2*MAX* + β_3 **MAX*HC + controls country means for problematic controls* + $\upsilon_i + \varepsilon_{it}$

(2B) PATENTS = β_1*HC* + β_2*MAX* + β_3 **MAX*HC + controls + +* $\upsilon_i + \varepsilon_{it}$

Estimation results are presented in Table 3. Model 0 omits the insurance variables, to gauge the apparent effect of HC on patenting when these variables are not included in the model. The estimated effect of HC is negative but small, and not statistically significant. This apparent irrelevance of HC to innovation parallels similar findings in the literature on HC and productivity (Krueger and Lindahl 2001).

[TABLE 3 ABOUT HERE]

The coefficients for Capital Stock, OPENNESS and, especially, R&D differ greatly between Model 1A and Model 1B. This is what we would expect for regressors which are relatively stable within countries over time: the country means included in 1A take out most of the variance of these variables, and leave relatively little to be explained by the year-to-year observations.

As the variables of interest in Models 1 and 2 are centered, the coefficients for the variables of interest may be interpreted as follows: in Models 1A and 1B, when EP and RR are at their means the marginal effect of HC on patenting remains negative, as it was in Model 0, but is now somewhat larger and, in Model 1A, statistically significant; the direct effect of EP is negative and statistically significant in both models - consistent with Barbosa and Faria's (2011) finding for European firms; RR's direct effect is negative, and significant in Model 1A, while much smaller, and statistically insignificant in Model 1B. The indirect (via HC) effect for EP is positive in 1A, negative in 1B, and statistically significant in neither, while the indirect effect of RR is positive and statistically significant in both 1A and 1B. This provides some encouragement for Danish-style flexicurity (high RR + low EP) policies. However, the instability of the coefficients between Models 1A and 1B is a matter of concern: we explore it further in Appendix 2, and on the whole are inclined not to put great weight on the model.

Both 2A and 2B show a negative and statistically significant direct effect on patenting from MAX, the stronger form of income insurance; the indirect effect, captured by the interaction HC*MAX, is negative and statistically significant in both 2A and 2B, consistent with H1 and contrary to H2.

The marginal effect of HC on PATENTS as MAX varies is shown in Figure 2: at low levels of insurance (i.e., of MAX), the effect of HC on PATENTS is negative and statistically significant; that negative effect fades away as MAX grows; at high levels of MAX the effect of HC on patenting is positive and again statistically significant. The positive and strongly significant coefficients on MAX*HC in 2A and 2B are almost double the size found for the RR*HC interaction in 1A and 1B. The difference between the effect at the lowest and highest levels of MAX is about 0.5, which is to say that when income insurance is at its highest level, a one SD improvement in the HC index yields patenting at a level about 0.5 SD higher than it would when income insurance is at its lowest level.[3]

[FIGURE 2 ABOUT HERE]

Figure 3 provides another way of interpreting the same result. It shows predicted (fitted) levels of PATENTS as a function of HC, at three different levels of MAX: the extremes (after winsorization) of the empirical distribution of MAX, and the median. In the first panel we see that when insurance is at its lowest, the effect of HC on PATENTS is negative; this would be consistent on a situation with 'more human capital' meaning credential races for safe generalist degrees that somehow actually harm innovation. At the median level of MAX, HC still has a negative effect, but a much weaker one. At the highest level of MAX, the effect of HC on PATENTS is positive.

[FIGURE 3 ABOUT HERE]

We can also infer variations in the direct effect of MAX on PATENTS, at different levels of HC. If we were to connect the curves where they meet the left hand borders of the three

[3] Our finding validates the results reported by Filippetti and Guy (2015). The two papers use starkly different measures of human capital (here a broad index; there, VET enrolments) and of innovation (here, a narrow and highly aggregated measure - patents at the national level; there, a broad measure - overall innovation investment – at the level of the firm). We use a different set of countries (adding non-European OECD countries, while losing a few from the former Soviet bloc), a long panel rather than a cross section, and a different estimation strategy. Despite all of these differences, the qualitative results are comparable.

panels, we would have a downward sloping curve (from 1 to about -0.8), indicating that at the lowest levels of HC found in our sample, insurance has a negative effect on PATENTS. If we perform the same exercise at the right hand margin of each panel, connecting the curves gives us an upward slope, running from about 0.5 to 1, indicating that at the highest levels of HC, insurance has an overall positive effect on PATENTS.

5. Conclusion

Our findings support the view that income insurance raises the marginal effect of HC on innovation. We argue that the reason for this is that stronger income insurance – both RR and EP - makes people more willing to take risks when investing in HC (i.e., studying), and that this produces in aggregate a more diverse portfolio of skills, and that this diversity is conducive to innovation. However, insurance has a negative direct effect on innovation. At low levels of HC, the negative direct effect substantially outweighs the positive effect; at the highest levels of HC, the positive effect outweighs the negative effect.

Even when the negative direct effect offsets (or more) the positive indirect effect, we believe the result is important. It tells us that income insurance affects the quality of human capital as an input to the innovation process: measured human capital has a different effect when insurance is high than when it is low. We do not know the reasons for the direct negative effect, and we do not know whether good institutional design might foster the positive indirect effect while mitigating the negative direct one. This might, however, be a good reading of what the Nordic countries have in fact done.

Our explanation for what we find comes in these steps. First, in keeping with evolutionary economic theory, we argue that diversity of skills is conducive to innovation. Second, we make a straightforward application of standard economic assumptions about human capital and about risk bearing: education is an investment, and risk-averse individuals, in the absence of insurance, go for safety; insurance encourages investment in skills for which future labor market demand appears less certain. Here we do make the assumption that when HC investments are less constrained by risk, the variety of investments across individuals increases.

At the basic level, this gives good reason to doubt the view held by many economists that the protection of incomes in the labour market comes at the cost of flexibility and efficiency. “Flexibility” is a property that can be assigned to many different economic functions: ability to adjust operations or employee numbers to changed demand is one such function, and the ability to identify and exploit opportunities for innovation is another. Similarly, efficiency may be viewed in static or dynamic terms, with the ability to innovate favouring the latter. Thus viewed, income insurance could well favour both flexibility and efficiency. Our results also help us to understand why, in the neo-liberal era, despite unprecedented and growing levels of measured educational attainment, employers in most countries complain of skill shortages (Cappelli 2014): as a means of stimulating the supply of specialist skills, pushing for higher educational attainment in the absence of income insurance is, to borrow a metaphor from macroeconomics, pushing on a string.

In a context of internationalized production and offshoring, our finding has an important industrial policy implication. Any industry or occupation which is potentially off-shorable is, *ipso facto*, one which offers highly uncertain demand for industry-specific skills. In the absence of strong insurance, this uncertainty is self-fulfilling: students and young workers will not invest in the skills required, skill shortages will ensue, and jobs will be offshored to countries which either provide the specialist skills either because they provide the insurance, or provide general-skill labor but at lower cost. Similar logic applies to automation, and to immigration of skilled labour: lack of income insurance will promote both.

Our variables EP and RR are vastly simplified proxies for complex institutional arrangements. Among these arrangements will be some for which the effect of insurance via HC is stronger (or weaker), and some for which the direct effect is weaker (or stronger). Fine-grained institutional and policy evaluation is needed in order to understand what makes the positive indirect effect of insurance (via HC) stronger, and what makes the negative direct effect weaker.

In addition to pointing up a clear need for finer-grained measures, our results have several empirical implications that can be tested in further research. One is that what we find for EP and RR should apply to other factors which serve as income insurance for individuals:

support for re-training (active labour market policies), or a relatively equitable distribution of family resources, to take two examples. Another is that insurance effects should be evident within sub-national, as well as national, labour markets - American states, German lander or, more generally, sub-national regions. A third is that what we have found for innovation should apply also to productivity growth.

TABLES AND FIGURES FOR THE TEXT

Table 1 –Variable definitions and sources

PATENTS	Log of per capital patent applications filed under the PCT - Inventor(s)'s country(ies) of residence .	OECD S&T database
Human capital (HC)	Proportion of population who have completed a tertiary degree (Barro and Lee, 2013)	Barro-Lee.com
Employment protection (EP)	Employment protection index OECD	OECD labour market database
Replacement rate (RR)	RRAPW: Net Unemployment Replacement Rate for an Average Production Worker, Single Person	(Van Vliet and Caminada, 2012)
MAX	For each observation, the greater of the standardized values of RR and EP	Authors' calculation
CAPITAL STOCK	Log of capital stock at constant 2005 national prices (in mil. 2005US$)	Penn Table
INFRASTRUCTURE	First principal component of the following variables: telecommunication revenue, electric power consumption, internet users, Mobile and fixed-line subscribers.	Cana Dataset (Castellacci and Natera 2011)
OPENNESS	Merchandise trade (% of GDP)	World Bank Development Indicators
R&D	Log of research expenditure (% of GDP)	Cana Dataset (Castellacci and Natera, 2011)

Figure 1

Employment Protection and Replacement Rate
25 year and 17 year subsamples

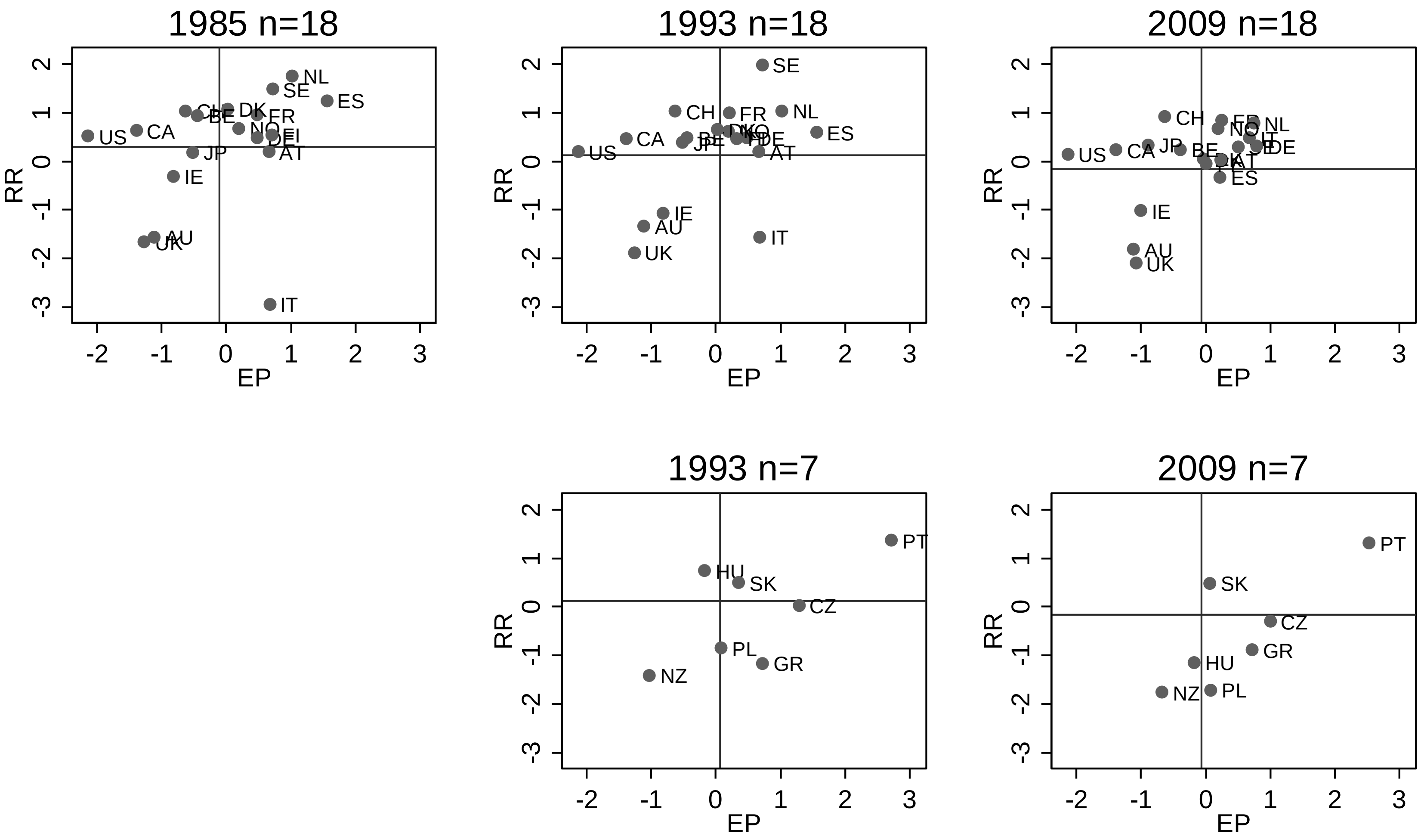


Table 2

Observations (years) in sample, by country

Table 2 – Correlation Matrix

	PATENTS	HC	RR	EP	MAX	OPENNESS	INFRASTRUCTURE	R&D	Capital Stock
PATENTS	1								
HC	0.317^{***}	1							
RR	0.0361	-0.172^{***}	1						
EP	-0.464^{***}	-0.536^{***}	0.358^{***}	1					
MAX	-0.263^{***}	-0.408^{***}	0.757^{***}	0.748^{***}	1				
OPENNESS	-0.226^{***}	0.190^{***}	0.102^{*}	0.108^{**}	0.0261	1			
INFRASTRUCTURE	0.455^{***}	0.560^{***}	-0.0240	-0.245^{***}	-0.190^{***}	0.106^{*}	1		
R&D	0.766^{***}	0.237^{***}	0.322^{***}	-0.378^{***}	-0.0995^{*}	-0.0850^{*}	0.331^{***}	1	
Capital Stock	0.666^{***}	0.239^{***}	0.218^{***}	-0.194^{***}	0.00506	-0.0920^{*}	0.559^{***}	0.609^{***}	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 Regression results

	Model 0	Model 1A	Model 1B	Model 2A	Model 2B
PATENTS					
HC	-0.028	-0.050*	-0.039	-0.028	-0.011
	(0.023)	(0.021)	(0.027)	(0.021)	(0.027)
RRw		-0.11***	-0.0070		
		(0.022)	(0.030)		
HC*RRw		0.025	0.032*		
		(0.013)	(0.016)		
EPw		-0.12***	-0.28***		
		(0.031)	(0.029)		
HC*EPw		0.025	-0.037		
		(0.016)	(0.019)		
MAXw				-0.13***	-0.13***
				(0.021)	(0.021)
HC*MAXw				0.071***	0.060***
				(0.013)	(0.015)
Capital Stock	0.16***	0.13***	0.28***	0.16***	0.24***
	(0.042)	(0.038)	(0.039)	(0.040)	(0.038)
R&D	0.026	0.032	0.34***	0.059	0.34***
	(0.047)	(0.045)	(0.042)	(0.046)	(0.038)
OPENNESS	0.0013	-0.022	-0.10***	-0.0039	-0.12**
	(0.031)	(0.029)	(0.031)	(0.031)	(0.042)
INFRASTRUCTURE	-0.13***	-0.0067	0.011	0.020	0.081*
	(0.029)	(0.030)	(0.033)	(0.032)	(0.039)
Mean CapStock	0.0035	0.073		-0.016	
	(0.065)	(0.062)		(0.074)	
Mean R&D	0.71***	0.78***		0.72***	
	(0.053)	(0.055)		(0.049)	
Mean OPEN	-0.40***	-0.35***		-0.44***	
	(0.052)	(0.046)		(0.055)	
Mean INFRA		-0.34***		-0.31***	
		(0.044)		(0.045)	
Observations	586	586	586	586	586
r2	0.87	0.89	0.85	0.92	0.90

Standard errors in parentheses
RR and EP winsorized at 2.5 SD from mean; this carries over to the calculation of MAX
Year dummies included in all models
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2

Marginal effect of HC on patenting, as MAX varies

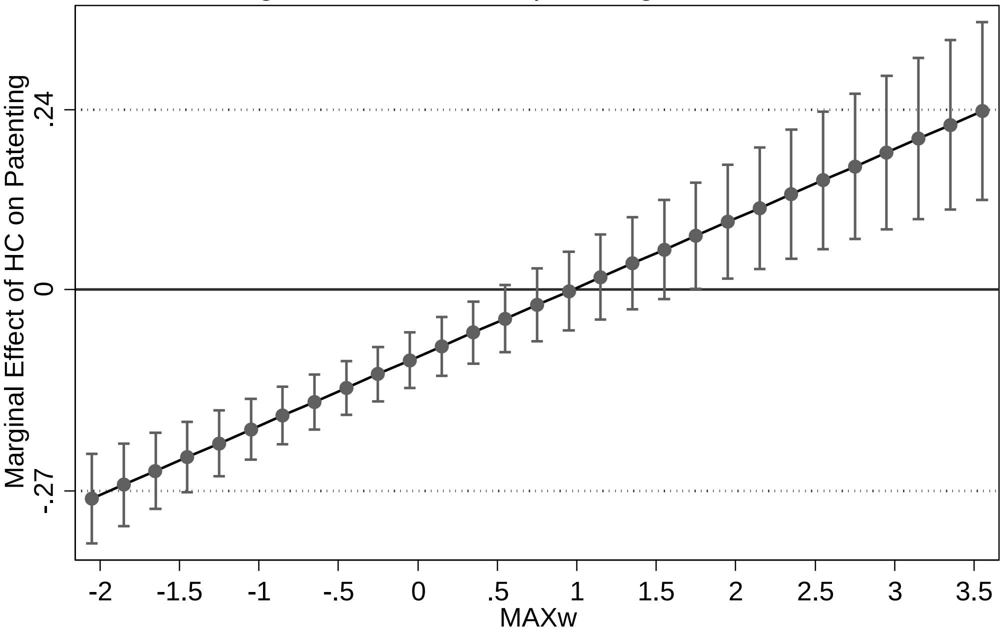
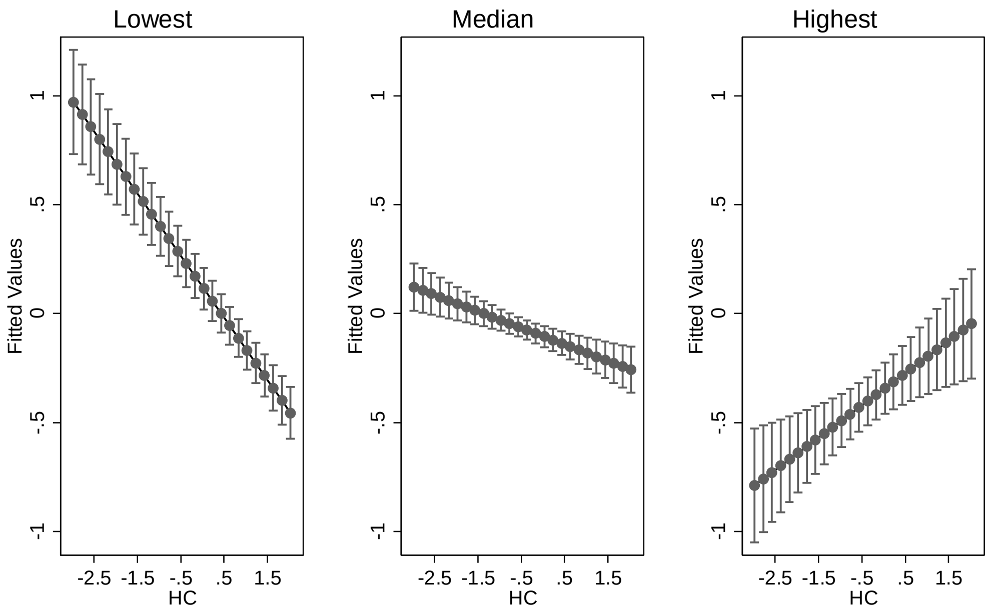


Figure 3

Patents as function of human capital, at three levels of income insurance



Appendix 1 –

Table A.1

Summary statistics for variables used in regressions

All variables transformed by standardization (zero mean, unit standard deviation). Winsorized (W) versions of EP and RR have been standardized; had values beyond +/- 2.5 SD from mean replaced by +/- 2.5 SD; then been re-standardized. MAX (W) is based on EP(W) and RR(W).

Variable		Mean	Std. Dev.	Min	Max
PATENTS	overall	0.00	1.00	-3.48	2.27
	between		0.88	-1.75	1.77
	within		0.53	-2.10	1.10
HC	overall	0.00	1.00	-2.97	2.08
	between		0.90	-1.87	1.60
	within		0.48	-2.47	2.02
RR	overall	0.00	1.00	-2.97	1.99
	between		0.96	-1.95	1.35
	within		0.33	-1.80	1.65
EP	overall	0.00	1.00	-2.14	3.19
	between		1.00	-2.14	2.76
	within		0.17	-0.53	0.80
RR(W)	overall	0.00	1.00	-2.52	2.00
	between		0.97	-1.97	1.36
	within		0.32	-1.42	1.59
EP(W)	overall	0.00	1.00	-2.19	2.58
	between		1.00	-2.19	2.58
	within		0.17	-0.55	0.82
MAX	overall	0.00	1.00	-2.05	3.27
	between		0.98	-1.96	2.76
	within		0.27	-0.89	1.09
MAX(W)	overall	0.00	1.00	-2.11	2.58
	between		0.98	-2.01	2.58
	within		0.28	-0.89	1.10
OPEN	overall	0.00	1.00	-1.41	4.00
	between		0.95	-1.27	2.59
	within		0.38	-1.47	1.65
INFRA	overall	0.00	1.00	-1.51	2.89
	between		0.55	-0.61	1.51
	within		0.84	-1.19	2.04
R&D	overall	0.00	1.00	-3.14	1.85
	between		0.98	-2.30	1.39
	within		0.33	-1.05	1.61
Capital Stock	overall	0.00	1.00	-2.71	2.10
	between		0.86	-2.16	1.10
	within		0.60	-1.89	2.14

Table A.2 - Observations (years) in sample, by country

Country	Observations
Australia	25
Austria	25
Belgium	25
Canada	25
Czech Republic	17
Denmark	25
Finland	25
France	25
Germany	25
Greece	22
Hungary	20
Ireland	25
Italy	25
Japan	25
Netherlands	25
New Zealand	20
Norway	25
Poland	18
Portugal	23
Slovak Republic	17
Spain	25
Sweden	25
Switzerland	25
United Kingdom	25
United States	25

Appendix 2: Estimation strategy, and outliers

2.1 Estimation strategy

We have a preference for using a random effects estimator because, for our purposes, we have two reasons for expecting the fixed effects estimates to be biased downwards. One is that our independent variables of interest (HC and the various insurance variables – RR, EP, MAX) are all crude approximations of the variables we would actually like to measure. The insurance variables, for instance, do not capture much of the critical detail of the institutional arrangements they are meant to measure: RR measures unemployment insurance for a single worker with representative earnings, but national policies vary with regard to whether the rate is different for a married worker, or a worker with children; to how the legal status of the separation from the employer affects eligibility; to whether the benefit is a flat rate or scaled to previous earnings, and if scaled with what floor and what cap; and so on. Even if these variables *were* able to capture such details of the insurance actually in place at a given time, our interest is in the workers' subjective assessment of the value of insurance – affected, for instance, by the level of confidence that the government will maintain the insurance in future decades. All of these factors can vary within a country from year to year, while the OECD continues to report a stable replacement rate or level of employment protection. Such errors in variables are known to bias fixed effects estimates towards zero (Griliches and Hausman 1986); Griliches and Hausman recommend using lagged values as instruments, but this solution is based on the assumption that the error is random from year to year (or within some period for which lagged values are available), while the errors we are dealing with may be persistent for many years – and in some cases are baked into indices (for EP in particular) that are entirely unchanged within a country for several years. A random effects estimator - a weighted average of fixed effects ("within") and between estimates - can reduce this source of bias.

The second reason for expecting downward bias from fixed effects is that the problem we are studying is an inherently dynamic one – one of intertemporal choice. Our data do not lend themselves to structural dynamic model of the problem; the between estimator, however, offers an economical way of capturing dynamic effects (Pesaran and Smith 1995).

The general problem with random effects estimators is that correlation between the group (country) effect and the regressors will bias estimates upwards (away from zero). Of course, such correlation may be a reflection of dynamic effects we actually want to pick up, but this is difficult to know. If we could ignore the problems discussed above, the fixed effects estimator would be unbiased. The most common solution to the bias problem, at least among economists, is a Hausman test which essentially asks whether the random effects estimates are statistically distinguishable from the fixed effects ones; in most cases, this leads to rejection of the random effects estimates (in our case, Stata can't compute the test result – also a common outcome with the Hausman test). Even when the fixed effects estimator is unbiased and the Hausman test fails, however, Clark and Linzer (2015) show that it is still quite possible, in a dataset the size of ours, for a random effects estimate to be preferable in terms of mean square error (MSE). The considerations they study are the dimensions (countries by time periods) of the dataset; the "sluggishness" of the regressors (is within-country variance much smaller than between country variance?); and the correlation between the regressors and the country effects. Applying their advice to our dataset and model, here is what we find: all of our regressors are sluggish, showing (in the transformed data) within-country variance at levels between 16 and 40% of overall variance, depending on the variable; other things equal, such sluggishness makes random effects problematic (Table A2.1). Although we note that it is exactly such sluggishness which makes the fixed effects estimator vulnerable to errors-in-variables bias, discussed above – a bias which goes the other way from that Clark and Linzer are concerned with - we continue on to Clark and Linzer's next step in the case of sluggish regressors, which is to consider the correlations between the regressors and the group effects. They recommend (2015, 404, fn. 6) approximating this with correlations between the group means of the regressors, and group effects from a fixed effects estimate. We estimated fixed effects versions of models (1) and (2). Correlations of the fixed effects with country means of the various regressors are shown in Table A2.2. The higher the correlation, the greater the bias in random effects estimates. The correlations with variables of interest (HC, the insurance variables and, in particular, the interactions of HC with the insurance variables) are mostly below 0.3, easily within a zone for which the choice between fixed- and random effects is close, in MSE terms, even if the conditions for fixed effects unbiasedness hold. The one exception is the correlation between EP and the fixed effect, which is in the range of 0.41-0.43.

[Table A2.1 about here]

[Table A2.2 about here]

For reasons we have given above, we don't believe the conditions for fixed effects to be unbiased *do* hold, and that would lead us decisively to favour the random effects estimates - but for one complication. The complication is that while our variables of interest are only weakly or moderately correlated with the country effects, the controls for R&D, Capital Stock, and Openness are strongly correlated. Another way of saying this is that for those variables, the within- and between estimates would be much different. The random effects estimates are weighted averages of the fixed effects and between estimates, designed produce coefficients which shrink the overall unexplained variance; but since the same weighting is applied to all variables, the presence of such strongly correlated controls affects the weighting used in computing the coefficients on variables of interest, pulling them closer to the between – and pooled cross section – end.

To obtain more conservative random effect estimates for our variables of interest, we adapt a strategy proposed by (Mundlak 1978, see also Imbens and Wooldridge 2007, Dieleman and Templin 2014). We can eliminate the effect of correlation between a control and the country effect by including in the random effects regression both the control and its mean by country. When the country mean of a variable is included, the coefficient on the individual variable becomes the fixed effects, or "within", estimate; more important, from our standpoint, is that the control variable's correlation with the group effect is no longer pulling the estimates of other coefficients in the "between" direction, which should make its estimates more conservative.

For the case with EP and RR, Table A2.3 compares pooled (OLS) estimates, fixed effects, random effects augmented with country means for the three strongly correlated controls (REM), and random effects without country means (RE). Table A2.4 does the same for MAX.

In both tables, a comparison of the coefficients on R&D across the four models provides a good illustration of some of the problems we've discussed above. Compared with both the pooled (OLS) estimates and the simple random effects without country means (RE), the fixed effects (FE) estimate for the effect of R&D on patents stands out as low, and statistically insignificant. Is this because the unbiased fixed effects estimate is stripping away biases and revealing to us that R&D spending has no measurable effect on patenting? If we look to the random effects model augmented by group means for the controls (REM), we see an answer: the country's average level of R&D does indeed have a large impact on patenting, but year-to-year within a country, differences in R&D aren't significantly related to patenting. In short, the relationship between R&D and patenting is a longer term, dynamic, one: REM separates the long-term effect from the immediate; OLS and RE lump the short-term and the long-term together; FE strips the long-term out.

[Table A2.3 about here]

[Table A2.4 about here]

2.2. Outliers

In A2.3, the estimates for the effects – both direct and indirect - of EP and RR appear a bit unstable: the HC*RR interaction is large in the OLS estimates, and effectively vanishes in the random effects estimates; the HC*EP interaction goes the other way; both interactions differ greatly between the RE and REM estimates. In contrast, in Table A2.4, the magnitude of the coefficient on HC*MAX changes little across OLS, RE and REM (for the reasons discussed above, we are not surprised that the FE estimate is consistently smaller).

One possible source of the instability of the EP and RR coefficients can be found in the distributions of our insurance variables: EP, RR and MAX all have long tails, which may be exercising disproportionate influence on our estimates, making them fragile in the face of changes in the estimator or the model specification. The long tails are especially pronounced for EP and MAX, which have a few very high values (Figure A2.1).

##Figure A2.1 about here##

Standard outlier diagnostics are not adapted to the estimators we use here, but we can check the influence of these outliers by simply winsorizing the variables at a conventional level of 2.5 standard deviations from the mean. We retrace our investigation of sluggishness (Table A2.1), and correlation of fixed effects and country means (Table A2.4), finding no new issues. We then re-estimate our regression models with the winsorized insurance variables. These are shown in Table A2.5 (for RR and EP) and A2.6 (for MAX). In the case of MAX, little changes – neither the direct effect nor the indirect is substantially affected, and the estimates remain stable across OLS, RE and REM. Estimates for RR change little, though the interaction of RR and HC now shows as significant in one model. Those for EP do change substantially as a result of winsorization, however: both the direct effect of EP, and its indirect effect via HC, are much smaller, and now statistically insignificant; in fact, they are about the same size as the estimates for RR, with a bit less than half the estimated effect size of MAX. Estimates for the HC*RR and HC*EP interactions are now more stable across OLS, RE and REM.

The improved stability of estimates when the EP and RR are winsorized leads us to trust the winsorized estimates more; for the models with MAX, the change makes little difference. In the paper, we use the winsorized variables.

[Table A2.5 about here]

[Table A2.6 about here]

Table A2.2

Correlation of country fixed effects with country means of regressors

Fixed effects for Raw from Tables A2.3 & A2.4; for Winsorized, from A2.5 & A2.6

	RAW			WINSORIZED	
	RR/EP	MAX		RR/EP	MAX
HC	0.0762	0.105*		0.104*	0.127**
EP	-0.407***			-0.431***	
RR	0.231***			0.221***	
HC*RR	0.0868*			0.278***	
HC*EP	0.269***			-0.0684	
MAX		-0.186***			-0.197***
HC*MAX		0.119**			0.318***
Capital stock	-0.0679	0.297***		0.586***	0.552***
R&D	0.584***	0.555***		0.798***	0.778***
OPEN	0.789***	0.777***		-0.426***	-0.447***
INFRA	-0.435***	-0.455***		0.152***	0.145***

Table A2.3 Alternate regression specifications for RR/EP-HC interactions

	1d:OLS	2d:FE	3d:REM	4d:RE
PATENTS				
HC	0.035	-0.00094	-0.058**	-0.046
	(0.082)	(0.036)	(0.022)	(0.028)
RR	-0.040	-0.089*	-0.095***	-0.00096
	(0.065)	(0.038)	(0.021)	(0.029)
HC*RR	0.12**	0.019	0.013	0.026
	(0.042)	(0.028)	(0.012)	(0.016)
EP	-0.19*	-0.080	-0.13***	-0.28***
	(0.084)	(0.069)	(0.030)	(0.028)
HC*EP	-0.072	0.071*	0.034	-0.032
	(0.048)	(0.029)	(0.018)	(0.020)
Capital Stock	0.20**	0.093	0.12***	0.27***
	(0.071)	(0.056)	(0.037)	(0.039)
R&D	0.63***	0.033	0.028	0.33***
	(0.082)	(0.048)	(0.045)	(0.041)
OPENNESS	-0.21**	-0.014	-0.020	-0.10**
	(0.059)	(0.040)	(0.029)	(0.032)
INFRASTRUCTURE	-0.32**	-0.0056	-0.0060	0.017
	(0.100)	(0.049)	(0.030)	(0.033)
Mean CapStock			0.073	
			(0.061)	
Mean R&D			0.77***	
			(0.054)	
Mean OPEN			-0.35***	
			(0.046)	
Mean INFRA			-0.33***	
			(0.044)	
Observations	586	561	586	586
r2	0.85		0.89	0.85

Standard errors in parentheses
1 REG w/ clustered s.e. 2. XTREGAR 3&4 XTPCSE w/ psar1
FE estimates lose one year (25 observations) for AR1 adjustment
Year dummies included in all models
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2.4 Alternate regression specifications for MAX-HC interaction

	1c:OLS	2c:FE	3c:RE	4c:RE
PATENTS				
HC	0.064	0.0095	-0.039	-0.013
	(0.12)	(0.035)	(0.022)	(0.028)
MAX	-0.15*	-0.055	-0.13***	-0.13***
	(0.063)	(0.039)	(0.020)	(0.022)
HC*MAX	0.053	0.059*	0.071***	0.054***
	(0.034)	(0.025)	(0.012)	(0.014)
Capital Stock	0.23**	0.097	0.16***	0.23***
	(0.073)	(0.056)	(0.039)	(0.038)
R&D	0.61***	0.036	0.059	0.34***
	(0.066)	(0.048)	(0.045)	(0.038)
OPENNESS	-0.27**	-0.000096	-0.0038	-0.11**
	(0.080)	(0.040)	(0.031)	(0.043)
INFRASTRUCTURE	-0.29*	-0.000074	0.022	0.081*
	(0.12)	(0.050)	(0.032)	(0.039)
Mean CapStock			-0.016	
			(0.073)	
Mean R&D			0.72***	
			(0.049)	
Mean OPEN			-0.44***	
			(0.055)	
Mean INFRA			-0.30***	
			(0.044)	
Observations	586	561	586	586
r2	0.83		0.93	0.91

Standard errors in parentheses
1 REG w/ clustered s.e. 2. XTREGAR 3&4 XTPCSE w/ psar1
FE estimates lose one year (25 observations) for AR1 adjustment
Year dummies included in all models
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2.5 Alternate regression specifications for RR/EP-HC interactions, raw vs. winsorized

	OLS (W)	FE (W)	REM (W)	REM (raw)	RE (W)	RE (raw)
HC	0.042	0.0039	-0.050*	-0.058**	-0.039	-0.046
	(0.082)	(0.036)	(0.021)	(0.022)	(0.027)	(0.028)
RR				-0.095***		-0.00096
				(0.021)		(0.029)
RRw	-0.052	-0.096*	-0.11***		-0.0070	
	(0.067)	(0.039)	(0.022)		(0.030)	
HC*RR				0.013		0.026
				(0.012)		(0.016)
HC*RRw	0.13**	0.028	0.025		0.032*	
	(0.045)	(0.029)	(0.013)		(0.016)	
EP				-0.13***		-0.28***
				(0.030)		(0.028)
EPw	-0.17	-0.047	-0.12***		-0.28***	
	(0.086)	(0.069)	(0.031)		(0.029)	
HC*EP				0.034		-0.032
				(0.018)		(0.020)
HC*EPw	-0.081	0.052	0.025		-0.037	
	(0.051)	(0.030)	(0.016)		(0.019)	
Capital Stock	0.20**	0.093	0.13***	0.12***	0.28***	0.27***
	(0.071)	(0.057)	(0.038)	(0.037)	(0.039)	(0.039)
R&D	0.64***	0.033	0.032	0.028	0.34***	0.33***
	(0.083)	(0.048)	(0.045)	(0.045)	(0.042)	(0.041)
OPENNESS	-0.20**	-0.012	-0.022	-0.020	-0.10***	-0.10**
	(0.060)	(0.040)	(0.029)	(0.029)	(0.031)	(0.032)
INFRASTRUCTURE	-0.32**	-0.0064	-0.0067	-0.0060	0.011	0.017
	(0.099)	(0.049)	(0.030)	(0.030)	(0.033)	(0.033)
Mean CapStock			0.073	0.073		
			(0.062)	(0.061)		
Mean R&D			0.78***	0.77***		
			(0.055)	(0.054)		
Mean OPEN			-0.35***	-0.35***		
			(0.046)	(0.046)		
Mean INFRA			-0.34***	-0.33***		
			(0.044)	(0.044)		
Observations	586	561	586	586	586	586
r2	0.85		0.89	0.89	0.85	0.85

Standard errors in parentheses
1 REG w/ clustered s.e. 2. XTREGAR 3&4 XTPCSE w/ psar1
FE estimates lose one year (25 observations) for AR1 adjustment
Year dummies included in all models
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

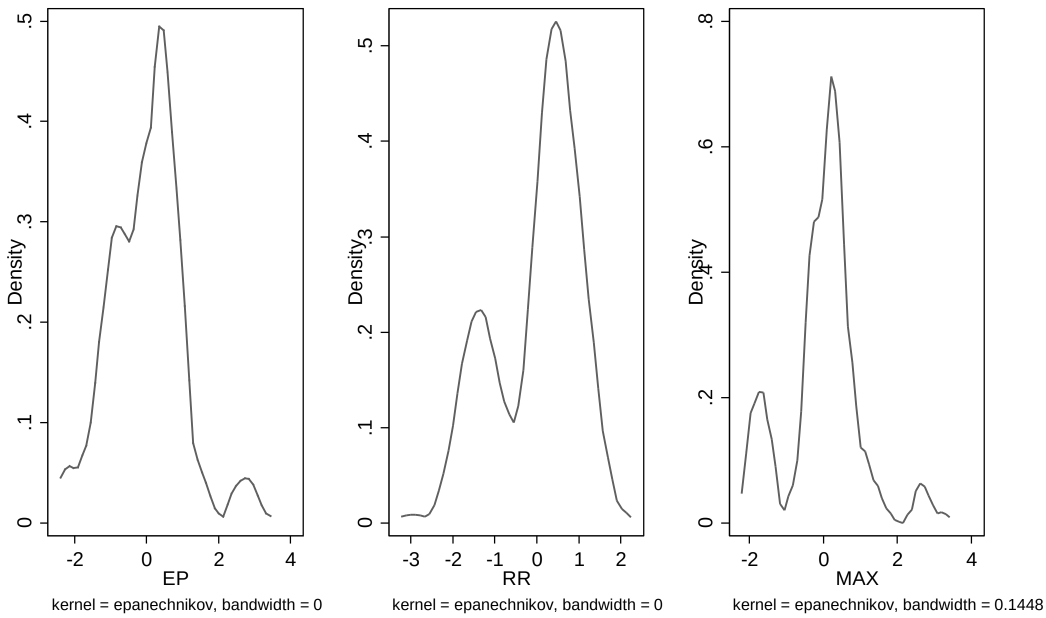
Table A2.6 Alternate regression specifications for MAX-HC interaction, raw vs. winsorized

	OLS (W)	FE (W)	REM (W)	REM (raw)
PATENTS				
HC	0.066	0.013	-0.028	-0.039
	(0.12)	(0.036)	(0.021)	(0.022)
MAX				-0.13^{***}
				(0.020)
MAXw	-0.15^{*}	-0.038	-0.13^{***}	
	(0.061)	(0.039)	(0.021)	
HC*MAX				0.071^{***}
				(0.012)
HC*MAXw	0.058	0.036	0.071^{***}	
	(0.036)	(0.026)	(0.013)	
Capital Stock	0.23^{**}	0.095	0.16^{***}	0.16^{***}
	(0.073)	(0.057)	(0.040)	(0.039)
R&D	0.61^{***}	0.038	0.059	0.059
	(0.066)	(0.048)	(0.046)	(0.045)
OPENNESS	-0.27^{**}	0.00042	-0.0039	-0.0038
	(0.080)	(0.040)	(0.031)	(0.031)
INFRASTRUCTURE	-0.30^{*}	-0.0042	0.020	0.022
	(0.12)	(0.050)	(0.032)	(0.032)
Mean CapStock			-0.016	-0.016
			(0.074)	(0.073)
Mean R&D			0.72^{***}	0.72^{***}
			(0.049)	(0.049)
Mean OPEN			-0.44^{***}	-0.44^{***}
			(0.055)	(0.055)
Mean INFRA			-0.31^{***}	-0.30^{***}
			(0.045)	(0.044)
Observations	586	561	586	586
r2	0.83		0.92	0.93

Standard errors in parentheses
1 REG w/ clustered s.e. 2. XTREGAR 3&4 XTPCSE w/ psar1
FE estimates lose one year (25 observations) for AR1 adjustment
Year dummies included in all models
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A2.1

Kernal Density Estimates for Insurance Variables



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