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# Labor market regulation, the diversity of knowledge and skill, and national innovation performance

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## Abstract

The diversity of knowledge and skill is an important element of a national system of innovation. We propose a theory of how certain labor market institutions affect diversity, and through that route affect levels of innovation. Specifically, unemployment protection (UP) encourages diversity by reducing the risk burden of a broad range of learning, or human capital investment; for that reason, UP fosters innovation. Employment protection (EP) reduces the risk burden of a much narrower range of learning; for this reason, it will not enhance diversity to the extent UP does, and it may actually depress overall diversity and innovation. Our approach differs from previous research on labor market insurance and skill formation, much of which has dealt with a distinction between general and specific skills, and which has treated the effects of UP and EP as similar. Estimating the effects of UP and EP on patenting for 25 OECD countries over 24 years, we find a positive effect from UP, a negative effect from EP, and evidence that the UP effect is mediated by diversity of skill.

**Keywords**: innovation, skills, human capital, evolutionary economics, unemployment insurance, active labor market policy, employment protection, social insurance, varieties of capitalism, national systems of innovation

**JEL code:** J24; O31.

## 1. Introduction

In this paper we examine the effect on innovation of labor market regulation (e.g. Wachsen and Blind, 2016; Kleinknecht et al., 2014). We are concerned with two broad categories of insurance provided by labor market regulation: laws and regulations which provide job security, called employment protection (EP); and public expenditure on support for the unemployed, including income support, retraining and various other measures, together called unemployment protection (UP). We develop a theory, and empirical evidence, that UP fosters innovation by enhancing the *diversity* of knowledge and skill in the workforce, while EP may actually reduce diversity and innovation. In doing so we help bridge a gap between the national systems of innovation (NSI) literature which places knowledge diversity at the center of innovation processes (e.g. Consoli and Rentocchini 2015), and the varieties of capitalism literature which deals with ways in which labor market regulation affects individual choices about education and training (Hanushek et al. 2017).

NSI research deals extensively with the ways in which the national education systems, technical and scientific institutions, and science and technology policies, can help to explain differences in innovation performance across countries (Lundvall, 2007). That and other streams of innovation research present theory and empirical evidence to support the view that diversity of knowledge and skill are conducive to innovation. This literature is largely silent, however, on way in which labor market institutions might affect such diversity (a rare exception are Holm et al (2010) and Filippetti and Guy (2015)).

UP and EP affect educational choices by providing insurance, encouraging students to study subjects which would otherwise be too risky in terms of job market outcomes. This feature of EP and UP is well understood in the political science-based varieties of capitalism literature (the seminar work here is Estevez-Abe et al., 2001), which locates risk in the *specificity* of a skill to an industry; the skills of interest are known to be in immediate demand, but uncertainty about the industry's future makes investment in a narrow skill risky[1]. When labor market institutions provide weaker insurance, students opt instead to learn more general skills, generality providing a form of self-insurance against changes in demand for skill. In this framework, EP and UP have been treated symmetrically: although in one case insurance is provided by the employer and in the other by the state, they have similar effects in encouraging the acquisition of specific skills with known immediate demand and uncertain futures.

Diversity of knowledge and skill, so important innovation literature at various levels of analysis (e.g. Landry and Wood 2012; Shin et al. 2012; Østergaard, Timmermans, and Kristinsson 2011; Herrmann and Peine 2011), is a different dimension from that of specificity-generality. A nation's stock of specific knowledge may be diverse,  or it may be focused in a few specialist areas; a nation's general knowledge may come via myriad paths through the arts, sciences, crafts and professions, or in a relatively homogeneous form due to a lot of students studying a single subject (management, say, or law) in much the same way.

Moreover, while the varieties of capitalism literature argues persuasively for symmetry in the effects of EP and UP on specific skills, we argue that the two forms of insurance may have divergent effects on diversity. UP will promote diversity of knowledge and skill, because it provides some protection even in the event that no good job market match is found in the short term; for that reason, it provides support for studies which are risky because they are either idiosyncratic - with unclear connection to immediate employment - or ambitious – with a clear short-term employment goal that the student has a good chance of failing to achieve. EP will produce less diversity than UP, because EP encourages a narrow focus on meeting known current needs of employers and getting a good (and lasting) job market match.

In section 2 we develop the theory outlined above, and locate it in the literature. Section 3 describes our data. In section 4, we employ two different strategies to estimate the relationships described by the theory. We use country-level data from a panel of OECD countries, with patents per capita as a measure of innovation. Our first strategy is to obtain

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[1] Similar considerations arise regarding specificity not to an industry but to an occupation, firm, or technology: simplifying somewhat we will, for brevity, say "industry-specific", or simply "specific".

estimates – without explicit mediation by diversity – of the overall relationship between UP, EP and innovation, using data on 25 OECD countries over a 24 year period. Consistent with our theory, we find a positive effect of UP on innovation, and a negative effect of EP. Second – for a sub-sample of 23 countries over 20 years - we estimate the extent to which these overall relationships are mediated by diversity, proxied by a measure of occupational diversity. We find that at least part of the UP-innovation relationship is mediated by diversity, but no evidence that the (negative) effect EP on innovation is mediated by diversity. Although the EP-innovation relationship requires further investigation, and a better measure of knowledge diversity would be welcome, these results do indicate a positive effect of UP on innovation, and are consistent with the proposition that this is due to enhanced diversity of knowledge and skill.

## 2. Background: labor market regulation, diversity of knowledge, and innovation

### 2.1 Labor market regulation and innovation

Studies of the effects of labor market regulation on innovation have focused largely on EP, seen on the one hand as the epitome of stifling labor market inflexibility, and on the other as creating an environment of long-term relationships in which both employees and employers are willing to invest in specific skills. Comparing European countries, Barbosa and Faria (2011) find that EP reduces the likelihood that firms will be classified as innovators in the Community Innovation Survey. Griffith and Macartney (2013) study patenting by multinational firms at different locations in Europe; they find that EP is positively associated with the raw count of patents, but negatively with a count weighted by the patent's citations of scientific journals. Wachsen and Blind (2016) find that the effect of numerical, or hire-and-fire labor market flexibility (weak EP) has positive effects on innovation in some settings, negative ones in others. 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. Other sources are usefully reviewed in by Wachsen and Blind (2016). Taken together, the studies of EP and innovation are inconclusive.

There is also a microdata literature which consistently finds a positive effect of employment security on innovation[2]. These are not, however, studies of the effect of EP institutions at the country level: rather, they examine situations in which employers have a choice about how much job security to offer, and find those offering more security to their staff to be more innovative. We cannot assume that what holds for individual firms also holds in aggregate when EP is enforced on all firms. In particular, individual firms voluntarily offering employment security may benefit from a selection effect in recruitment of workers; there may also be a selection effect among the firms themselves, with those best able to benefit from a stable workforce offering job security.

A few studies have viewed EP jointly with the second pillar of insurance in the labor market, which is UP. In Holm et al (2010), EP and UP appear together in one variable, derived by principal components analysis, in which UP has a positive weight and EP a negative one; they use this as a measure of flexible security. Holm et al find that flexible security is positively related to what they call "discretionary learning organization", a set of organizational practices associated with innovation (Arundel et al., 2007). Filippetti and Guy (2015) show that vocational education has a positive effect on innovation when UP (measured as the earnings replacement rate of benefits for some typical worker) is strong. However, their study is limited to innovation in a cross-section of European countries during the recent financial crisis.

While empirical studies of UP – with or without EP – and innovation are few, there is a substantial body of theory associating insurance in the labor market, together with complementary financial market and political institutions, with *types* of innovation. Hall and Soskice (2001) argue that coordinated market economies (CMEs, which have strong UP, EP, or both) have a comparative advantage in incremental innovation, while liberal market economies (LMEs, with low social security) have a comparative advantage in radical innovation. As an empirical generalization about national innovation systems, the Hall-Soskice identification of radical innovation with general skills and incremental innovation with specific ones has proven

[2] (Kleinknecht et al., 2014; Lucidi and Kleinknecht, 2010; Michie and Quinn, 2002; Michie and Sheehan, 2005, 1999; Zhou et al., 2011).

problematic (Akkermans et al., 2009; Herrmann and Peine, 2011; Taylor, 2004). Be that as it may, the Hall-Soskice framework does not predict any *overall* innovation advantage associated with levels of UP or EP.

Like EP, UP has often been seen as a source of labor market inflexibility, in this case offering life on the dole; reducing the value of jobless benefits in order to raise the difference between unemployment benefit and income from employment is seen as fostering "a preference for work" (Bó et al., 2018). Whether for this reason or simply due to budgetary constraints, typical levels of UP today are far lower than they were thirty years ago (Figure 1). Yet, from the 1990s on, relatively *strong* UP, together with weak EP has been championed by the Danish government as flexible security, or "flexicurity". Since the mid-2000s this has also been a flagship policy of the European Commission, included in the Lisbon Agenda, restated in the EU2020 Strategy, became pervasive in European Union (EU) policy such as the European Employment Strategy, and is also at the basis of policy advice given to EU countries within the European Semester.[3] The importance of labor market insurance together with its contested status, add to the reasons we need to understand whether and how insurance in the labor market affects innovation.

[FIGURE 1 HERE]

Summing up, existing empirical literature on EP and innovation is inconclusive, while that on UP and innovation is scant. UP is often seen as playing a role similar to EP, either as a source of inflexibility or, in the Hall-Soskice framework, as fostering investment in specific skills; in contrast, the logic behind flexible security sees UP and EP as having opposing effects.

## 2.2 How insurance in the labor market can generate diversity of knowledge and of skill

For the individual, an investment in human capital is risky: it is irreversible, opportunities for diversification are limited, and the market demand for the individual's knowledge or skill may be volatile. For this reason choices about human capital investment will be affected by

[3] See here for more information: https://ec.europa.eu/social/main.jsp?catId=102&langId=en.

insurance provided in the labor market. With weak insurance, workers under-invest in human capital (Krebs, 2003); of more interest here, weak insurance directs investment toward relatively safe knowledge or skills (Carneiro and Heckman, 2002; Saks and Shore, 2005).

Risk is not uni-dimensional, however, and UP and EP address different *kinds* of human capital risk. It is useful here to distinguish between two categories of risk. One involves human capital investments which are safe in the short term, but are risky due to uncertainty about future demand; the other involves skills and knowledge for which immediate demand is uncertain (this includes situations in which uncertainty pervades in both the short- and long terms).

Short term safety with future uncertainty is often attached to skills which are specific to a particular industry, occupation, or firm. Vocational education and training (VET) qualifications are often specific in this way: they provide better than average immediate employment prospects, but a greater long-term risk of unemployment (Hanushek et al., 2017; Lamo et al., 2011). It is easy to see how the internationalization of production, with the ever-present threat that an industry or occupation might be off-shored, magnifies this kind of risk.

In many cases, demand for one's knowledge or skill is uncertain not only in the long term but also in the short. A student might do deep studies in geography out of simple fascination with the subject, despite great uncertainty about the short-term employment prospects for geographers; a student might aspire to a career in the arts, sport, or scientific research – knowing that the odds of making a living at it are small; an industry important in the student's locality might appear ripe for off-shoring, raising the prospect that industry-specific skills learned this year might never translate into a job.

Either UP or EP can de-risk investments of the first type – ones for which there is known immediate demand, but highly uncertain future demand. If, at some point in the future, demand for a worker's skill and knowledge falls and the worker loses her job, UP supports her during job search or re-training; if the same worker were protected by EP, the employer would have to choose between continuing to pay wages to an unproductive employee, paying for retraining, or making a severance payment sufficient to induce the employee to leave the firm.

The mechanisms are different, but EP and UP should have similar effects on willingness to invest in skills specific to an industry. For this reason Estevez-Abe et al (2001) associate both with the acquisition of risky industry-specific skills, and show that both UP and EP are associated with high levels of enrollment in VET. In a parallel literature which ignores UP altogether, low-insurance economies are commonly associated with heavy investment in general skills, and high EP economies with specific ones (Krueger and Kumar, 2004a, 2004b; Roe, 2003).

UP and EP differ greatly, however, when short term uncertainty is high. If a worker has studied something which does not immediately lead to a good job, UP can help her move to a better job in the future. Holm et al (2010) emphasize this aspect of UP when they associate flexible security with the discretionary learning organization.

The value of EP, on the other hand, is precisely that it helps one keep the job one has, so it only as valuable as that job. Thus, far from freeing students to follow ambitious or idiosyncratic paths, EP enforces courses of study known to lead to immediate secure employment. In addition to encouraging investment in industry-specific skills, the firm-specific insurance value of EP intensifies competition for entry level jobs with the more desirable employers; among those aspiring to work for large employers offering long term prospects, this encourages convergence on a few conventional courses of study – a phenomenon often noted in connection with the winner-take-all career systems of Japan, France and South Korea (Aoki, 1988; Yoo and Lee, 2009). The queueing at the ports of entry of the most desirable employers spills backward to university and school admissions (Frank and Cook, 1995).

Summing up, both UP and EP will enhance investment in specific skills for which long-term demand is uncertain. UP will also encourage investment in knowledge and skill for which the immediate demand is uncertain. For this reason, UP unambiguously enhances the diversity of knowledge and skill.

What we propose above is a choice-led theory of knowledge and skill. In framing the question this way, we abstract from the ways the design of a country’s education and training system might affect choices about what to learn, independent of both insurance in the labor market and student choice. In effect, our assumption is that for a given level of educational resource, students will find ways either to explore or to conform, and that the salient variation in these choices will depend on what the students see being rewarded or punished in the labor market.

### 2.3 From diversity to innovation

Diversity is a fundamental source for knowledge-driven transformation at different levels: at the firm, industry and sectoral levels; at the cluster or regional system of innovation level; and at the NSI level (Consoli and Rentocchini 2015). There are two distinct reasons for this: selection among innovations, and integration of fields of knowledge.

In a changing environment which throws up new problems and opportunities, a diverse repertoire of possible responses makes it more likely that a good solution will be found. Selection of innovations may be through market competition between firms (Alchian, 1950), or through administrative processes within firms or other organizations. Innovations also often require the integration of different technologies, different competencies, or different approaches.

While we can think of either of these in terms of a biological analogue – natural selection in the first instance, the relative robustness of biodiverse ecosystems in the second – in applying them to innovation we also need to bear in mind that diversity of knowledge can help people who are working together consciously to solve a problem, whether within a firm, in a network of firms, or sitting down for coffee in one of the fabled creative clusters. See, for instance, the account Arundel et al (2007) give of discretionary learning organizations [DLO], which provides the basis for Holm et al's (2010) claim that diverse knowledge fostered by flexible security favours the DLO.

This contribution of diversity to innovation is fundamental to NSI theory. Metcalfe (1995) tells us that innovation is enhanced by having institutions that "generate diversity in the behaviour, in that diversity generates the range of available innovations" (p. 28). His reasoning is evolutionary: "traditionally two questions have defined the scope for evolutionary analysis: the origin of variety and the nature of selection" (Metcalfe, 1995, p. 29). Innovation is conceptualized as a searching and learning process in an uncertainty environment. Diversity is a characteristic of systems that evolve as a result of "the continuous appearance of various forms of novelty" (Dosi, 1997, p. 1531).

Once the importance of variety for innovation is recognized, it becomes crucial to identify those policies that generate and sustain variety over time: "this leads us directly to the idea of technology systems and national systems of innovation" (Metcalfe, 1995 p. 30). The capacity to generate diversity is a distinct feature of NSI; innovation systems have been defined in terms of "how different national systems create diversity, reproduce routines and select firms, products and routines" (Lundvall, 2007 p. 101). Particularly during periods of intense change, there are fundamental advantages to diversity, since "a technological monoculture may be more dangerous than an ecological monoculture"; therefore, policies should encourage "local originality and diversity" (Freeman, 1995; p. 18). Diversity has also been also seen as an aspect of national absorptive capacity, which helps inward technology transfer (Mowery and Oxley, 1997).

There is evidence of the diversity of knowledge contributing to innovation at various sub-national scales. We see it in supply chain relationships (Malerba, 2002; Mowery and Nelson, 1999; Pavitt, 1984); due to spatial proximity, as in the cases of regional innovation systems (Asheim and Coenen, 2005; Cooke et al., 1997); and in clusters generally (Iammarino and McCann, 2006; Kamnungwut and Guy, ). The role of proximity in the creative joining of diverse knowledge figures large in urban studies, where the *diversity dividend* for innovation (e.g. Desrochers and Leppälä, 2011; Landry and Wood, 2012) builds on Jacobs' (1961) insights.

There is also good evidence for the contribution to innovation of diverse knowledge and skill within the firm (Shin et al., 2012; Herstad et al. 2019; Solheim et al. 2020). We can think of diversity as characteristic of a reservoir of 'slack' in knowledge and skill that may at some point become useful for the generation or absorption of innovation. Levinthal and March (1993, 103) tell us that it is valuable for firms to create "inventories of competencies" that might be employed later; firms need to know more than they make (Brusoni et al. 2001). Within-firm diversity of employees' educational backgrounds improves innovation performance of firms (Herrmann and Peine, 2011; Østergaard et al., 2011).

Even at the level of the individual, recent research points to the importance of diverse portfolios of non-routine skills (Consoli et al., 2016; Consoli and Rentocchini, 2015), with social skills playing a complementary role with cognitive skills (Deming 2017; Deming and Kahn 2017).

The NSI approach takes these different levels as elements in a system: firms are treated as the primary actors in the generation of innovation (and of patenting activity); the innovation performance of firms depends not only on their internal resources and R&D activities, but also benefits also from the system in which they are embedded, and particularly from the accumulation of knowledge and skill developed outside their boundaries, in such other agents as suppliers or customers, or in research institutions and universities. Hence, a diversified national portfolio of skills provides a broader spectrum of competences for firms to exploit, both within and outside their core technological domains (Laursen and Salter, 2006; O'Really and Tushman, 2004).

## 3. Data

Our data are all at country level. We begin with data for 28 OECD countries. For three of these we have data for only six years, while for the remaining 25 we have between 18 and 24 years of data; as we cannot plausibly treat the omitted years of the three as missing at random, we drop them from the sample, leaving the 25 countries with 572 observations from 1990 to 2013; we use this for the initial overall estimates. For the mediation model, which can be understood as a decomposition of the overall model, we lose two countries, and keeping time series of approximately the same length loses us four years, leaving 23 countries and 442 observations from 1994 to 2013.

The countries and years covered by the dataset are shown in Table 1. Variable descriptions are in Table 2, and descriptive statistics in Table 3 (correlations are provided in Appendix 6).

[TABLE 1 ABOUT HERE]

[TABLE 2 ABOUT HERE]

[TABLE 3 ABOUT HERE]

Our measure of innovation is international Patent Cooperation Treaty (PCT) patents applications (PATENTS). PCT applications are “international” 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). In our dataset, the reference country for PCT applications is the inventor’s country of residence.[4]

The use of patents to measure innovative performance of countries must come with several caveats. Not all innovations are associated with patents, and not all patents lead to new products or processes in the first place. 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 (Archibugi and Pianta, 1992; Schmookler, 1962). In our case we note, first, that an international patent application is costly and time consuming, so it is worthwhile only for those innovations for which companies expect high return from them. Second, the PCT procedure is common to each country; this would reduce measurement error due to differences in the propensity to apply. Third, our empirical models include year and country fixed effects to account for other sources of heterogeneity; see Furman et al. (2002) on the use of international patents and a fixed effects model to address a similar problem. Further,

[4] In the case of cooperation among inventors from different countries patents are attributed to each country mentioned on the basis of fractional counts.

research has shown that only a fraction of innovation gets patented, while a sizeable share remains covered by industrial secrecy (Archibugi and Pianta 1992). We remain conscious that patents are an imperfect measure of actual innovation activity, and that they are also used for rent seeking. Yet, patents represent "the only observable manifestation of inventive activity with a well-grounded claim for universality" (Trajtenberg, 1990).

There are three main types of patent statistics: patents filed with individual countries' patent offices; international patent applications, also referred to as 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. First, 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). Second, 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, measures of international patenting have been increasingly employed in studies on countries innovation performance. We use data from PCT rather than triadic patent applications because the latter tend to be rarer especially for less advanced countries.

As explanatory variables we need measures of labor market insurance available over time and comparable across countries, both for UP and EP.

We define UP as the share of per capita GDP represented by a country's combined spending per unemployed person on active and passive labor market policies (ALMP and PLMP, respectively). The OECD provides two measures of total ALMP expenditure, one measure including benefit administration and job placement services, the other not. We use the latter, more restrictive, measure because administration and placement were unreported in some countries for several years. ALMP includes expenditures on training, employment incentives, sheltered and supported employment and rehabilitation (for disabled), direct job creation, and start-up incentives. PLMP includes expenditure on unemployment benefits, redundancy compensation, bankruptcy compensation, and early retirement (OECD, 2015).

ALMP and PLMP are of course not the same thing, and as policy instruments each has its advocates. Yet, when we look at them side by side, we see that in practice governments do not actually make much choice between them – they move together. In logarithmic form (as used for estimation), the correlation of ALMP and PLMP is 0.95 (Appendix 1).

An alternative measure of unemployment protection is an index of the earnings replacement rate (RR) of PLMP. PLMP benefits can vary by marital status, dependent children, industry, type of employment contract, previous income, duration of most recent employment, duration of unemployment and so on, so an RR index is calculated for some particular type of worker. We were not able to obtain an RR index calculated on a consistent basis for the years and countries of our sample. In any case, we think it preferable to use the share of GDP spent on labor market policy (active and passive) per unemployed person, as this avoids focus on one arbitrary type of worker.

Employment protection legislation (EP) includes "the entire set of regulations that place some limits to the faculties of firms to hire and fire workers, even if they are not grounded primarily in the law, but originate from the collective bargaining of the social partners, or are a consequence of court rulings" (Barone, 2001, p.4). The OECD prepared several variants of its EP index; we use the broadest, the Strictness of Employment Protection Index. This is compiled from 21 different items covering different aspects of employment protection regulations, covering in particular three broad dimensions: *1)* individual dismissal of workers with regular contracts; *2)* costs for collective dismissals; *3)* regulation of temporary contracts (OECD, 2014).

As with any effort to reduce a complex phenomenon to an index, this has limitations. The index reflects laws and regulations, but not variations in enforcement; protections vary by such factors as occupation or firm size; it misses the informal economy, whose importance varies across countries, and thus tends to overstate the level of protection in countries with high shares of either informal, legally or de facto unprotected employment (Aleksynska and Eberlein, 2016; Myant and Brandhuber, 2016).

The OECD index deals only with formal institutions; it does not capture employment protection offered voluntarily by companies, for instance in the internal labor markets in large firms in countries with weak EP (Aoki, 1988; Doeringer and Piore, 1971). This is appropriate for studying the effects of formal institutions as we are doing, but it must be noted that individual choices about skill acquisition presumably also take informal institutions into account. One way to get a comprehensive measure of employment protection would be to use an outcome measure, such as the OECD's measure of average job tenure; but, while tenure is affected by employment protection (formal and informal) it is endogenously affected by other factors as well – including, probably, skill. We must, in the end, settle for the EP index we have.

To estimate the effect of labor market insurance on innovation we need to control for other factors we would expect to contribute to innovation performance at the country level. We use fixed capital stock to control for the level of economic development and also the industrial structure of the country (e.g. Evangelista, 1999); we use this rather than GDP because the latter would be a plausible dependent variable in a similar regression - a post-treatment confounder, or what Angrist and Pischke (2009, pp 64-68) call a "bad control". R&D expenditure is an important direct input to innovation and in particular to patenting. We also control for education expenditure per capita. Finally, we include the shares employment in agriculture, manufacturing, and services to capture changes in industry structure over the period of study.

For our mediation estimates, we unfortunately have no direct measure of the supply of knowledge or skill diversity. We use a proxy from the demand side based on the occupational classification provided by the statistical office of the International Labor Organization (ILO), (ILO, 2012).[5] As a measure of occupational diversity, we use the inverse of the Herfindal index

[5] The International Standard Classification of Occupations 2008 (ISCO-08) provides a system for classifying and aggregating occupational information obtained by means of statistical censuses and surveys, as well as from administrative records. ISCO-08 is a four-level hierarchically structured classification that allows all jobs in the world to be classified into 436 unit groups. These groups form the most detailed level of the classification structure and are aggregated into 130 minor groups, 43 sub-major groups and 10 major groups, based on their similarity in

of ten broad occupational categories, listed in Appendix Table A1; higher values of this variable reflect greater heterogeneity in the composition of the occupations within a country.

Several limitations to this measure need to be noted. First, the ILO data provides the only internationally comparable data on occupations, but with only ten categories this is a coarse measure. Second, this is a demand side variable while our theory is about the supply of skill diversity. Third, an underlying assumption is that diversity in occupation reflects diversity in human capital demanded, and if the market clears this reflects diversity in the human capital supplied. However, more diversity in demand can mean new advanced tasks (requiring new skills) added to the national portfolio, but it can also mean an increased division of labor. To the extent that the latter falls across two occupational categories, this will increase our index of occupational diversity. Arguably, this could have a positive effect on innovation due to increased division of labor rather than increased skill diversity. While we do not have a way of resolving this problem entirely, use of broad occupational categories would seem to mitigate it.[6]

## 4. Estimation strategy and results

We can think of our problem as estimating the effect of labor market institutions (UP and EP) on innovation (patents), with the effect mediated by the diversity of the workforce's knowledge and skill. Formally, this gives us three equations. The first, estimated without the mediator, is for the overall effect of the institutions on innovation:

$$PATENTS_{it} = \beta_1 UP_{it} + \beta_2 EP_{it} + \gamma Z0_{it} + c_i + \lambda_t + u_{it} \quad (1)$$

terms of the skill level and skill specialization required for the jobs. This allows the production of relatively detailed internationally comparable data as well as summary information for only 10 groups at the highest level of aggregation.

[6] We constructed a more fine-grained measure, PIACC Occupational Diversity, based on the PIACC Survey of Adult Skills. This, however, is available only for 2013 and only for fourteen countries, precluding use in our regression analysis. The PIACC diversity measure is positively correlated with our measure of diversity (0.45), and UP (0.2); while it is negatively correlated with EP (-0.16).

The second and third incorporate the mediator, and decompose the overall effect into direct and indirect effects (Imai et al., 2010):

$$PATENTS_{it} = \alpha DIVERSITY_{it} + \xi_1 UP_{it} + \xi_2 EP_{it} + \gamma Z1_{it} + c_i + \lambda_t + u_{it} \quad (2a)$$

$$DIVERSITY_{it} = \delta_1 UP_{it} + \delta_2 EP_{it} + \mu Z2_{it} + c_i + \lambda_t + \varepsilon_{it} \quad (2b)$$

This yields an estimate of the average causal mediated effect (ACME) effect of the UP or EP on patenting:

$$\delta_j * \alpha \quad (2c)$$

For either variable UP (j=1) or EP (j=2), the estimate of the average direct effect (ADE) effect is $\xi_j$, and the average total effect (ATE) is:

$$\Theta_j = \xi_j + \delta_j * \alpha \quad (2d)$$

When the controls – Z0, Z1 and Z2 - are the same in the three equations, then $\Theta_j = \beta_i$.

In all three equations, *i* is an index for country, *t* an index for year, *u* is an error term, $\lambda$ is the time (year) effect, and *c* is the country effect. The country effect controls for unobserved country-specific variables, while the time dummy controls for any common trend or shock. The inclusion of country and time effects allows us to use country-level data and a sparse set of controls – and, thus, to use relatively long time series and a large enough cross section of countries that we can fruitfully study the effects of country-level institutional variables.

## 4.1 Overall estimates

We begin by estimating the overall effects of UP and EP on innovation. We do this for two reasons: inclusion of the mediation variable reduces our sample size, and the overall model allows us to use both more efficient estimators, and dynamic estimators, that are not available for the mediation model.

Models such as (1) present the choice of treating the country effect ($c_i$) as fixed or as random; the latter makes use of more information and is thus more efficient, but it suffers from bias if the $u_{it}$ are correlated with $c_i$. A standard approach to resolving this choice is the Hausman test, but that is not applicable with time dummies in the model. The Hausman test is also all-or-nothing – as if random effects estimates must be used either for all regressors, or for none. We follow, instead, the correlated random effects approach of Mundlak (1978), and include as additional regressors the country means for each variable (see also Wooldridge, 2010). This gives us (1a):

$$PATENTS_{it} = \beta_1 UP_{it} + \beta_2 EP_{it} + \gamma Z_{it} + \eta M_i + c_i + \lambda_t + u_{it} \qquad (1a)$$

$M_i$ is a vector of country means for UP, EP and all controls – call this $K$ variables, and K country means, overall. (1a) is estimated assuming random effects. A random effects estimator normally yields a weighted average of within-group (fixed effect) and between-group effects, but with Mundlak's specification the group means control for the between-group effects, leaving the coefficients on UP, EP and Z as fixed effects estimates. In 1a, the coefficients $\eta_1 \ldots \eta_K$ on $M_1 \ldots M_K$ provide tests, variable by variable, for the random effects assumptions: if the coefficient for the country mean of some variable $k$ ($M_k$) is statistically insignificant, we do not reject the null hypothesis of no correlation between variable $K$ and the country effect. We can then drop some or all of the non-significant $M_k$ from the model, so long as we can reject the joint significance of the set of $M_k$ we are dropping. The model we obtain through this process is (1b). We then estimate (1b), again using random effects. In (1b), the coefficients for variables for which we have kept the country means are still the fixed effects estimates, while those for which we have dropped the country means are now the more efficient random effects estimates.

Table 4 shows pooled OLS estimates (i.e., neither country fixed effects nor country means in the model) in the first column; fixed effects estimates of (1) in the second column; random effects estimates (1a) in the third; and random effects estimates (1b) in the last column. The OLS estimates are biased due to the omission of country effects; (1), (1a) and (1b) should all be free of that bias, and also from bias from correlation between variables and the country effect; of these latter three, (1b) provides a more efficient estimate for the effect of UP, and for that reason is to be preferred.

[TABLE 4 ABOUT HERE]

In column 4 (model 1b), we see that UP has a positive effect on innovation. As both PATENTS and UP are scalar variables in logarithmic form, the coefficient on UP is an elasticity: a 1% increase in UP is associated with a 0.17% increase in patenting; the coefficient is statistically significant at 0.05. Note that Mundlak's test, in allowing us to drop the country mean, is saying that within-country changes and between country differences in UP have comparable empirical associations with patenting. The country mean of EP is statistically significant in (1a), indicating between-country differences attributable to unobserved country-specific variables; we must therefore keep the mean in the model, which is to say that we use the fixed effects estimate for the effect of EP on innovation. The latter is negative, and significant at the 0.001 level: consulting Tables 3 and 4 together, we can see that a one s.d. increase in EP is associated with a 0.23 s.d. reduction in patenting[7].

There are reasons to be cautious about the EP finding. Previous research on EP legislation and innovation has yielded mixed results, discussed in Section 2 above; the limitations of the EP index as a measure, discussed in Section 3; and the fact that many studies of firm-level or (subnational) state-level EP policies have found positive effects of EP on innovation[8]. It is also possible that EP, compared to UP, creates stronger incentives to keep innovation secret since workers tend to be within the firm for a longer time, thus leading to a lower inclination to patenting.

Two questions about this modelling strategy are worth noting: one to do with dynamics, the other with possible multi-collinearity.

If, as our theory suggests, UP and EP affect educational choices, with an effect on the skill and knowledge of the workforce which in turn affects innovation, we would expect the effect to unfold over time. Shouldn't we be lagging UP and EP? Perhaps, but then by how many years? Given the nature of the hypothesized dynamic problem, this would take us quickly beyond the resources of the standard fixed- and random effects estimators, and of the tools available for

[7] (-0.579*0.86)/2.18=0.228

[8] We had been concerned about that fact that the within-country variation of EP appeared to be dominated by large changes in a few countries. Jackknife analysis, however, finds no country to be an influential outlier. See Appendix Table A3.

the mediation models in the next section. For that reason we have stuck with a static approach in all models.

We have, however, explored the problem of dynamics using the pooled mean group estimator of Pesaran et al (1999). This approach requires using fewer controls as it entails estimating an error correction model for each country as a time series, and for that reason the results are not directly comparable. The differences, however, are striking: the long-run mean group estimate for UP is roughly double that in Table 4 (model 1b); that for EP is comparable to the fixed effects estimates from 1b. All are strongly statistically significant (see Appendix 4). This suggests that the static estimates reported in Table 4, especially for UP, are conservative.

The multicollinearity question arises from the fact that the three principal controls – R&D expenditure, education expenditure, and capital stock per capita – are very highly corelated. If the model is correct, this means we must live with large standard errors, but does not diminish the variables' value as controls (Goldberger, 1991, pp. 246–248); pairwise correlation with the variables of interest is lower, and the estimated effects for these variables are large enough that they are statistically significant despite any imprecision introduced by multicollinearity. Multicollinearitymight open the question of whether our "testing down" in the Mundlak model – which allows us to eliminate the country mean for UP and use the random effects estimate for UP – may be benefiting from large standard errors; we note, however, that the failure to reject the null (zero) hypothesis for the country means of UP, is not even close – the p value is 0.55.

For the standard errors reported in all tables, we use the Liang-Zeger cluster correction. As Abadie et al. (2017) show, this method is conservative. We should note, however, that the results supporting its use are asymptotic, its small sample (we have 25 or 23 clusters, depending on the model) properties unknown. If we use a more general Huber-White correction instead, statistical significance levels for UP and EP in both the overall estimates and the mediation estimates (below) take on much higher level of significance.

## 4.2 Mediation estimates

As noted above, the mediation estimates are a decomposition of the overall effect into direct (labor market institutions to patenting) and indirect (mediated by diversity). These relationships are shown schematically in Figure 2.

[FIGURE 2 HERE]

Our theory deals with the indirect effects. The estimator also allows direct effects for both UP and EP. In the case of EP, there are ample theories and previous empirical results predicting direct effects on innovation, either positive or negative; in the case of UP, there is no support for a direct effect in the literature. However, by construction, the estimated direct effect is any part of the overall effect (equation 1) *not* picked up in the estimated indirect effect. With our data, we would not expect the estimated indirect effect of either UP or EP to account for the entire overall effect: as noted above, our variable for diversity is a rough proxy – it is occupation, not knowledge or skill, and it is very coarse, based on just nine categories. We therefore expect to see indirect effects if our theory holds, and direct effects in any event[9].

Estimates are reported in Table 5. The first column reports 2a, the direct estimates from the mediation model. The second column reports estimates for the mediation equation, 2b. 2c, the estimate of the average causal mediation effect (ACME) for both UP and EP, is in the third column. The overall effects of UP and EP as estimated from equations 2a and 2b, are shown in the fourth column; these are, as they should be, the same as the fixed effects estimates for the same sample (fifth column). The sixth column reports the Mundlak estimates for the mediation sample – in the case of UP, random effects.

[TABLE 5 HERE]

[9] Under our hypothesis, the effect of UP and EP on knowledge and skill begins with educational choices made before entering the workforce. Immigrant workers, however, have often received their educations elsewhere, presumably not informed by the labor market institutions of the country in which they now reside; moreover, having been educated elsewhere they likely contribute to the diversity of knowledge and skill in any case (Davenport 2004). Our data is not well suited for taking this into account, but we have run the mediation estimates with the immigrant share of the population as an additional predictor for diversity. Its effect is small and statistically insignificant, and it has only negligible effects on other coefficients and their standard errors.

Note that, in this smaller sample, the overall effect of UP is no longer statistically significant. The loss of significance is not surprising, not only because of the smaller N, but also because the variables of interest all display lower variances in the smaller sample (Table 3). Similarly, in Eq 2a, the effect of UP on DIVERSITY falls just short of statistical significance, while that of EP is nowhere close (p values of 0.058 and 0.091, respectively).

What is of concern to us, however, is not the size or statistical significance of the component parts, but the ACME (Eq 2c) itself (Imai et al., 2010). Despite the weakness of the proxy and the reduced size and variability of the sample, the ACME for UP is statistically significant at the 0.05 level, providing evidence for mediation of the UP-patenting relationship by diversity. For EP, however, the ACME is not statistically significant.

Our estimates assume sequential ignorability – the independence of the error terms of the direct relationship (2a) and the mediation equation (2b). This assumption cannot be tested directly, but Hicks and Tingley (2011) provide a tool, based on Imai et al (2010), for graphical analysis of the sensitivity of the ACME estimates to violations of the assumption. This is shown in Appendix 5; there are no conventions for interpreting the acceptable tolerance to violations of independence, but we take what we find as satisfactory.

## 5. Discussion and conclusions

Here we interpret our findings, first in terms of the simple statistical relationships shown; second, with reference to labor market policy; third, with respect to our interpretation that, by promoting diversity, UP promotes innovation. We finally discuss some limitations of the paper and conclude.

Our estimates of the overall relationship show that a substantial positive effect of UP on patenting. We also find positive mediation of the UP-innovation relationship by occupational diversity, a proxy for knowledge and skill diversity. We find a negative relationship between EP and innovation, but no evidence that relationship is mediated by diversity.

Holm et al (2010) suggest that flexible security is good for innovation. This is consistent with our findings, although we must caution that proponents of flexicurity often have particular UP instruments in mind, while we deal here simply with aggregate spending. We need also to draw attention to the apparent *independence* of the UP and EP effects. While in Holm et al flexible security is constructed as a single variable, in our analysis UP and EP are examined as distinct independent variables. Empirically, independence appears to be an appropriate representation: the correlation between the two is low (0.23); dropping either variable from our regression has little effect on the coefficient on the other. Filippetti and Guy (2015), in a cross-sectional study, find that *either* UP or EP is complementary with vocational training in sustaining innovation, but that EP and UP are not themselves complementary. In light of this, we cannot say that we have found that flexible security, *as a package*, is conducive to innovation; rather, we have found that spending on UP is conducive to innovation, and that lower levels of EP may *also* be conducive to innovation.

These findings imply that UP, at least, should be regarded as part of a country's innovation policy toolkit. Along with other arguments for robust levels of UP – e.g., social cohesion (Bó et al., 2018); – low unemployment and high productivity growth (Viebrock and Clasen, 2009) – it invites a question about the wisdom of governments driving down UP payments per unemployed person as a share of GDP, to half their 1995 level.

Part of the causal explanation we propose for our finding – that innovation benefits from diversity of knowledge – is well established. The other part of it – that UP will actively promote diversity of knowledge, while EP may reduce it – is as far as we know new, though consistent with the insights of Holm et al (2010).

Our analysis is limited by the data we use. The strength of our approach is that we are able to study the effect of country-level institutions in a panel of reasonable time and cross-sectional dimensions. This of course puts certain constraints on our choice of variables. Finer-grained evidence (at the industry, say, or firm level) could potentially afford a stronger test of our hypothesis, and better exploration of causal paths at different levels, but would doubtless do so at the cost of reduced coverage across countries and over time.

As in most work in the social sciences, all of our measures are proxies for the phenomena of theoretical interest, and so must at best be regarded as measurements made with error. Two of our measures are particularly problematic. First, EP is a limited measure of employment protection – but the best we have. Second, the lack of data on diversity of knowledge and skill leaves us with a proxy which measures not diversity of human capital, but (at best) the demand for such diversity. If we assume that educational choice is affected both by insurance and labor demand, with insurance encouraging risk-taking and demand imposing a constraint, then we would expect a stronger direct relationship between insurance and variety of knowledge and skill supplied than between insurance and variety of occupations. For that reason we expect that the mediation model in the present paper underestimates the strength of the insurance-variety link, although what implications that would have for the diversity-innovation link we cannot say. The coarseness of the proxy (few categories, aggregated at country level) is a distinct issue, and this requires interpreting our results from the mediation model as a starting point for research on this issue.

Finally, in examining the effect of labor market insurance on innovation, we have viewed the problem almost entirely through the lens of choices made by workers and students. We do control for education expenditure but we have not addressed ways in which the structure of the education and training systems might affect the diversity or homogeneity of knowledge and skill. Beyond that, we rely on the country effects to pick up differences in educational systems (along with other unobserved institutional features). Given the crucial role played by education in the NSI research, there remains the question of how much of knowledge diversity, or of skill specificity, can be explained not by student choice *within* the education system but by the *structure* of the education system.

This is worth exploring in future research, in that the contemporary rhetoric of education policy is overwhelmingly one of matching students' knowledge and skill with known employer needs.

Education policy debates about how to accomplish that range along the specificity-generality dimension: is it better to focus on meeting the specific needs identified by employers (e.g. through apprenticeships and VET), or to provide better access to general, transferable skills? A proposition suggested by our results is that such energetic attempts to match educational attainments with known employer needs may, for purposes of innovation at least, be self-defeating. We might instead learn something from 18th century German university reformers: Von Humboldt and others then promoted, as a tool for what we would call industrial policy and innovation, a system of education and research based not on meeting known employer needs, but on individually-driven free inquiry (Menand et al., 2017) – perhaps a recipe, if complemented by an appropriate insurance system, for diversity of knowledge and for innovation.

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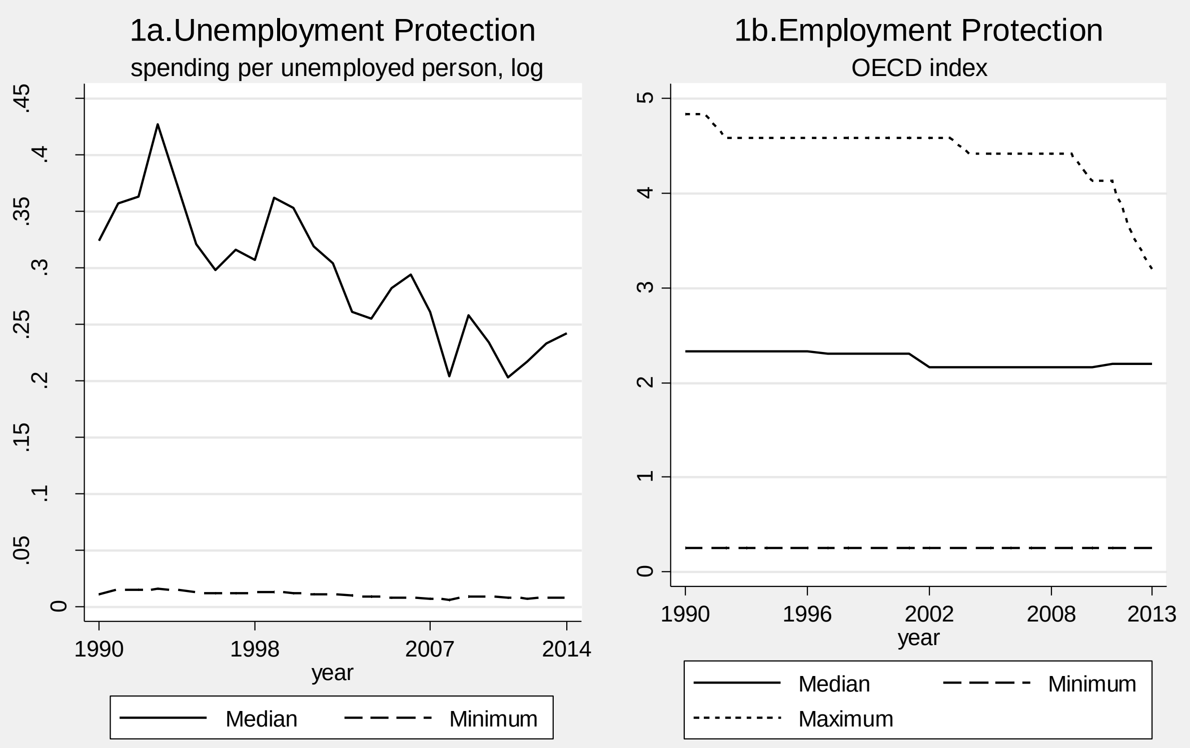
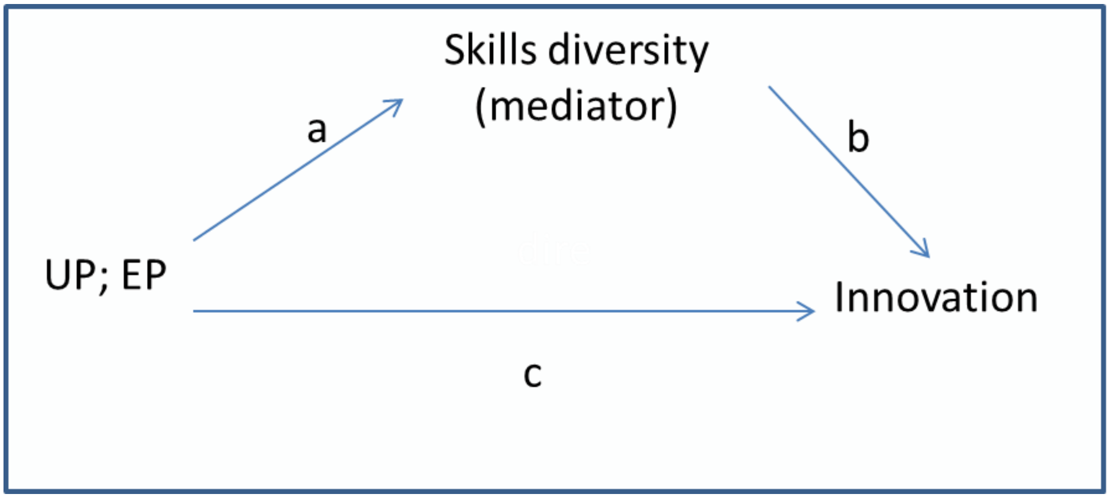
## Figures for the text

**Figure 1 – UP and EP median levels for 17 OECD countries**




Showing balanced panel: countries with missing years included in estimates but excluded from graphs.
UP shown here in levels; log levels used in estimates. Maximum UP is off graph scale.

**Figure 2 – the direct and indirect effect of labor market regulation on innovation**



## Tables for the text

### Table 1 –Variable descriptions and sources

| Variable | Description | Sources |
|---|---|---|
| **Patents** | Log of per capita patent applications filed under the PCT - Inventor(s)'s country(ies) of residence. | OECD S&T database, Main Science and Technology Indicators |
| **Unemployment protection (UP)** | These OECD variables are reported as expenditure/GDP:<br>• Passive labor market policy (PLMP) item 120 (categories 80 & 90).<br>• Active labor market policy (ALMP) item 112, a subtotal including categories 20-70 only. (This omits category 10, Placement services & benefit administration, which has a large number of missing observations.)<br>UP is the log of expenditure per unemployed person, scaled by GDP per capita:<br>ln[(Expenditure/Unemployed persons) / (GDP/Pop)] | OECD Public expenditure and participant stocks on LMP: Public expenditure as percent of GDP. |
| **Employment protection (EP)** | Employment protection index OECD: Strictness of employment protection – individual and collective dismissals (regular contracts) | OECD labour market database |
| **Occupation diversity** | Inverse of Herfindal Index (HI) calculated from International Standard Classification of Occupation (ISCO) data as follows: ln(1/HI) | ILOSTAT |
| **Capital Stock** | Log of per capita capital stock at constant 2005 national prices (in mil. 2005US$) | Penn Table |
| **Education expenditure** | Log of general government expenditure on education (current, capital, and transfers) per capita | World Bank Development Indicators; UNESCO Institute for Statistics |
| **R&D** | Log of per capita expenditure in research and development | OECD S&T database |
| **Agriculture** | Employment in agriculture (% of total employment) | World Bank Development Indicators; |
| **Industry** | Employment in industry (% of total employment) | World Bank Development Indicators; |
| **Services** | Employment in services (% of total employment) | World Bank Development Indicators; |

**Table 2 - Countries in samples**

| **Mediation sample** |
|---|
| Australia |
| Austria |
| Belgium |
| Canada |
| Czech Republic |
| Denmark |
| Finland |
| France |
| Germany |
| Greece |
| Hungary |
| Ireland |
| Italy |
| Netherlands |
| New Zealand |
| Norway |
| Poland |
| Portugal |
| Slovakia |
| Spain |
| Sweden |
| Switzerland |
| United Kingdom |
| |
| **Additional countries in overall sample** |
| Japan |
| United States |

**Table 3 - Descriptive statistics**

| | Overall panel, for model 1 | | Smaller panel for mediation model | |
|---|---|---|---|---|
| **Variable** | Mean | SD | Mean | SD |
| **Patents** | -9.62 | 2.18 | -9.60 | 2.12 |
| **UP** | -1.37 | 1.88 | -1.29 | 1.84 |
| **EP** | 2.14 | 0.86 | 2.25 | 0.76 |
| **R&D** | -7.25 | 1.90 | -7.32 | 1.83 |
| **Capital Stock** | -1.90 | 1.73 | -1.92 | 1.69 |
| **Education expenditure** | 7.40 | 1.81 | 7.39 | 1.80 |
| **Agriculture** | 5.35 | 3.75 | 5.09 | 3.45 |
| **Manufacturing** | 26.69 | 6.42 | 26.16 | 6.43 |
| **Services** | 67.33 | 8.30 | 68.12 | 7.76 |
| **Diversity** | | | 1.32 | 0.11 |
| | | | | |
| **N** | 572 | | 442 | |
| **Countries** | 25 | | 23 | |
| **Years** | 1990-2013 | | 1994-2013 | |

**Table 4 – Estimates for overall effect. Dependent variable: patents per capita**

| | OLS | (1) Fixed Effects | (1a) Mundlak | (1b) Mundlak |
|---|---|---|---|---|
| UP | 0.301$^{**}$ | 0.149$^{+}$ | 0.149$^{+}$ | 0.173$^{*}$ |
| | (0.100) | (0.083) | (0.084) | (0.076) |
| UP M | | | 0.082 | |
| | | | (0.138) | |
| EP | -0.266$^{*}$ | -0.578$^{**}$ | -0.579$^{***}$ | -0.566$^{***}$ |
| | (0.109) | (0.161) | (0.161) | (0.162) |
| EP M | | | 0.390$^{**}$ | 0.424$^{*}$ |
| | | | (0.149) | (0.175) |
| R&D | 1.100$^{***}$ | 0.249 | 0.250 | 0.225 |
| | (0.165) | (0.244) | (0.246) | (0.246) |
| R&D M | | | 1.125$^{*}$ | 1.382$^{***}$ |
| | | | (0.437) | (0.369) |
| Capital Stock | -0.019 | 0.737$^{*}$ | 0.740$^{*}$ | 0.760$^{**}$ |
| | (0.253) | (0.294) | (0.295) | (0.282) |
| Cap Stock M | | | -1.161$^{**}$ | -1.178$^{***}$ |
| | | | (0.429) | (0.356) |
| Education expenditure | 0.203 | -0.071 | -0.068 | -0.055 |
| | (0.185) | (0.290) | (0.292) | (0.265) |
| Ed Exp M | | | 0.290 | |
| | | | (0.462) | |
| Agriculture | -0.001 | -0.035$^{*}$ | -0.035$^{*}$ | -0.026$^{+}$ |
| | (0.018) | (0.016) | (0.016) | (0.014) |
| Agriculture M | | | 0.056$^{*}$ | |
| | | | (0.025) | |
| Manufacturing | 0.025$^{+}$ | 0.012 | 0.012 | 0.016 |
| | (0.013) | (0.017) | (0.018) | (0.014) |
| Mfg M | | | 0.002 | |
| | | | (0.028) | |
| Observations | 572 | 572 | 572 | 572 |
| R squared | 0.956 | 0.872 | | |
| R squared (overall) | | 0.865 | 0.963 | 0.956 |
| R squared (within) | | 0.872 | 0.872 | 0.872 |

Note: Standard errors in parentheses; Year dummies included in all models; standard errors clustered by country
$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

**Table 5 - Estimates for mediation sample. Dependent variable: patents per capita**

| | Mediation model | | | | | |
|---|---|---|---|---|---|---|
| | Eq 2a Patents (Direct) | Eq 2b Diversity (Mediator) | **Eq 2c Patents (ACME)** | Eq 2d Patents (Overall) | Eq 1 Patents (F.E.) | Eq 1b Patents (Mundlak) |
| Diversity | 1.898* | | | | | |
| | (0.804) | | | | | |
| UP | 0.071 | 0.019+ | **0.035*** | 0.106 | 0.106 | 0.133+ |
| | (0.082) | (0.010) | **(0.017)** | (0.077) | (0.079) | (0.076) |
| EP | -0.381*** | -0.062+ | **-0.118** | -0.499*** | -0.499** | -0.472*** |
| | (0.097) | (0.037) | **(0.081)** | (0.132) | (0.136) | (0.138) |
| R&D | 0.571** | -0.006 | | | 0.558* | 0.520* |
| | (0.206) | (0.043) | | | (0.258) | (0.263) |
| Capital Stock | 0.137 | 0.038 | | | 0.212 | 0.309 |
| | (0.262) | (0.074) | | | (0.323) | (0.315) |
| Education expenditure | 0.102 | 0.048 | | | 0.192 | 0.137 |
| | (0.164) | (0.035) | | | (0.223) | (0.199) |
| Agriculture | -0.047* | 0.001 | | | -0.045* | -0.013 |
| | (0.021) | (0.005) | | | (0.019) | (0.017) |
| Manufacturing | -0.011 | 0.000 | | | -0.010 | 0.005 |
| | (0.015) | (0.005) | | | (0.017) | (0.012) |
| Observations | 442 | 442 | 442 | 442 | 442 | 442 |
| R2 overall | | | | | 0.895 | 0.965 |
| R2 within | | | | | 0.841 | 0.838 |

Note: country fixed effects and year dummies included, country means in Mundlak estimates; standard errors clustered by country; goodness of fit measures not available for the mediation model, estimated using GSEM in Stata.

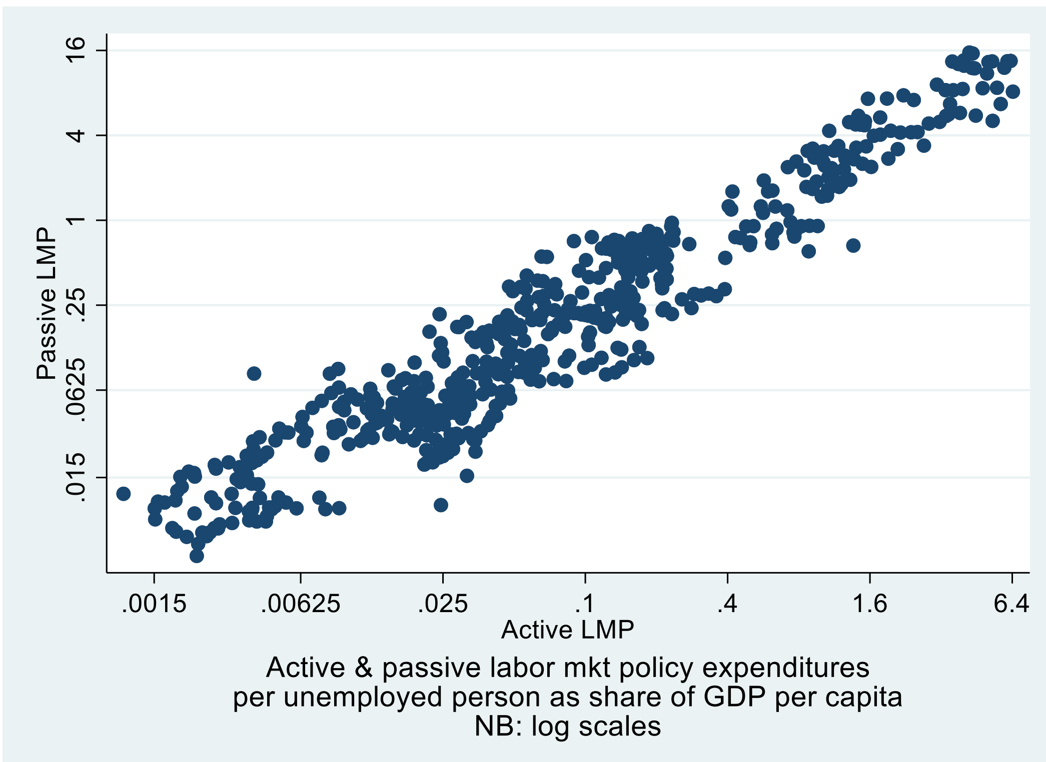
+ p<0.10; * p<0.05; ** p<0.01; *** p<0.001.

## Technical appendix to "Labor market regulation, diversity of knowledge and skill, and national innovation performance", Andrea Filippetti and Frederick Guy, 2019

### Appendix 1. Correlation of active and passive labor market policy expenditures

Our variable UP is the natural logarithm of labor market policy expenditure per unemployed worker as a share of per capita GDP. This includes the OECD's categories of active and passive labor market policy expenditures. As noted in the text of the paper, the two measures are very highly correlated (r=0.95).

**Figure A1.1**



## Appendix 2 - Occupational diversity measure

**Table A2** - Employment by occupation according to both the categories of the latest version of the ISCO available and aggregate categories

| Broad Skill Levels | Aggregate Categories of Occupation | ISCO-08 |
|---|---|---|
| **Skill levels 3 and 4 (high)** | *Managers, professionals, and technicians* | 1. Legislators, senior officials and managers<br>2. Professionals<br>3. Technicians and associate professionals |
| **Skill level 2 (medium)** | *Clerical, service, and sales workers* | 4. Clerks<br>5. Service workers and shop and market sales workers |
| | *Skilled agricultural and trades workers* | 6. Skilled agricultural and fishery workers<br>7. Craft and related trades workers |
| | *Plant and machine operators, and assemblers* | 8. Plant and machine operators and assemblers |
| **Skill level 1 (low)** | *Elementary occupations* | 9. Elementary occupations |
| **Armed forces** | *Armed forces occupations* | 0. Armed forces |

Source: ILO 2012.

## Appendix 3

**Table A3.1 Within-country and between-country variance**

| Variable | | Sample for reduced form estimates (N=572) Mean | Std. Dev. | Sample for mediation estimates (N=442) Mean | Std. Dev. |
|---|---|---|---|---|---|
| Patents | overall | -9.62 | 2.18 | -9.60 | 2.12 |
| | between | | 2.11 | | 2.13 |
| | within | | 0.69 | | 0.47 |
| UP | overall | -1.37 | 1.88 | -1.29 | 1.84 |
| | between | | 1.88 | | 1.90 |
| | within | | 0.29 | | 0.27 |
| EP | overall | 2.14 | 0.86 | 2.25 | 0.76 |
| | between | | 0.85 | | 0.76 |
| | within | | 0.16 | | 0.14 |
| R&D | overall | -7.25 | 1.90 | -7.32 | 1.83 |
| | between | | 1.91 | | 1.90 |
| | within | | 0.28 | | 0.24 |
| Capital Stock | overall | -1.90 | 1.73 | -1.92 | 1.69 |
| | between | | 1.72 | | 1.75 |
| | within | | 0.29 | | 0.27 |
| Education | overall | 7.40 | 1.81 | 7.39 | 1.80 |
| | between | | 1.79 | | 1.83 |
| | within | | 0.41 | | 0.37 |
| Agriculture | overall | 5.35 | 3.75 | 5.09 | 3.45 |
| | between | | 3.36 | | 3.26 |
| | within | | 1.71 | | 1.19 |
| Manufacturing | overall | 26.69 | 6.42 | 26.16 | 6.43 |
| | between | | 5.94 | | 6.09 |
| | within | | 2.84 | | 2.37 |
| Diversity | overall | | | 1.32 | 0.11 |
| | between | | | | 0.09 |
| | within | | | | 0.06 |

**Table A3.2 – Sensitivity to choice of countries in sample: jackknife estimates of influence of individual countries**

| EP - fixed effects | | | UP - fixed effects | | | UP - random effects ( | |
|---|---|---|---|---|---|---|---|
| country | | | country | | | country | |
| ALL | -0.578 | | | 0.149 | | | 0.173 |
| | Δβ | | | Δβ | | | Δβ |
| Portugal | -0.08965 | | Poland | -0.04449 | | Poland | -0.04503 |
| Australia | -0.08854 | | New Zeala | -0.0351 | | New Zeala | -0.04393 |
| Japan | -0.04707 | | Slovakia | -0.02741 | | Slovakia | -0.02773 |
| United Kin | -0.02967 | | United Sta | -0.0166 | | Hungary | -0.01475 |
| Czech Rep | -0.02169 | | Hungary | -0.01514 | | Finland | -0.01285 |
| Denmark | -0.02048 | | Finland | -0.01274 | | United Sta | -0.00889 |
| Greece | -0.01156 | | Australia | -0.00951 | | Belgium | -0.00758 |
| Hungary | -0.009 | | Japan | -0.00722 | | France | -0.00714 |
| Netherlan | -0.00781 | | France | -0.00686 | | Australia | -0.00562 |
| United Sta | -0.00453 | | Switzerlan | -0.00583 | | Switzerlan | -0.0042 |
| Poland | -0.00406 | | Belgium | -0.00423 | | Germany | -0.00278 |
| France | -0.00324 | | Canada | -0.00226 | | Norway | -0.00274 |
| Italy | -0.00137 | | Germany | -0.00082 | | Canada | -0.00086 |
| Switzerlan | -0.00104 | | Norway | 0.00016 | | Austria | 0.001206 |
| Belgium | -0.00012 | | Austria | 0.002009 | | Denmark | 0.004886 |
| Canada | 0.001067 | | Ireland | 0.005519 | | Japan | 0.005546 |
| Ireland | 0.002602 | | Denmark | 0.006391 | | Ireland | 0.006079 |
| Germany | 0.004001 | | Italy | 0.008119 | | Czech Rep | 0.007033 |
| Austria | 0.008856 | | Greece | 0.008857 | | Greece | 0.011086 |
| Norway | 0.010397 | | Spain | 0.016284 | | Spain | 0.01303 |
| Slovakia | 0.020299 | | Netherlan | 0.016698 | | Italy | 0.016215 |
| Sweden | 0.042146 | | Portugal | 0.016705 | | Netherlan | 0.017983 |
| New Zeala | 0.05124 | | United Kin | 0.028501 | | United Kin | 0.018991 |
| Finland | 0.058009 | | Czech Rep | 0.032417 | | Portugal | 0.02622 |
| Spain | 0.150773 | | Sweden | 0.048754 | | Sweden | 0.040037 |

ALL is estimate of β when all countries are included (from Table 3 in the paper). Δβ is change in coefficient estimate when country is excluded from sample.

## Appendix 4 – Long-run estimates allowing for between-country heterogeneity in innovation response to labor market regulations

**Table A 4.1**
Pooled mean group estimates

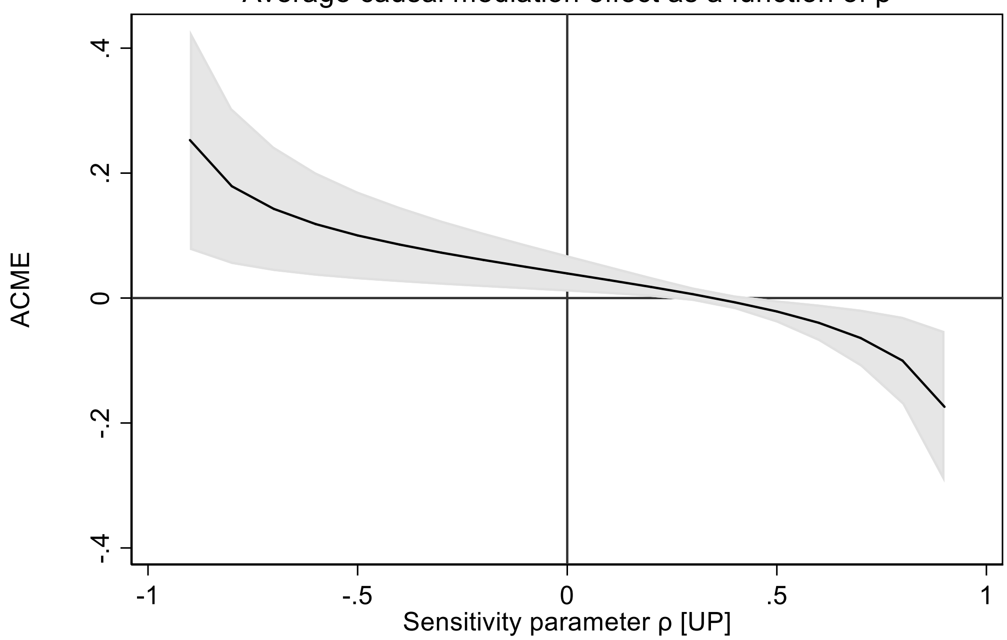
| | (1) D.Patents |
|---|---|
| Long run effects | |
| UP | 0.310$^{**}$ |
| | (0.103) |
| EP | -0.588$^{*}$ |
| | (0.299) |
| R&D | 0.611$^{***}$ |
| | (0.153) |
| Short run effects | |
| __ec | -0.189$^{***}$ |
| | (0.0229) |
| D.UP | -0.0283 |
| | (0.0380) |
| D.EP | -0.0465 |
| | (0.108) |
| D.R&D | 0.333$^{*}$ |
| | (0.140) |
| D.Agriculture | -0.0695 |
| | (0.0721) |
| D.Manufacturing | 0.0342$^{***}$ |
| | (0.0102) |
| Constant | -0.635$^{***}$ |
| | (0.128) |
| Observations | 547 |

Standard errors in parentheses
$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

## Appendix 5 – Sensitivity of UP ACME estimate to violation of sequential ignorability assumption

Figure A5.1

Average causal mediation effect as a function of ρ




The model assumes independence of the error terms of (2a) and (2b) – which is to say that ρ, their correlation, is zero. This cannot be verified directly, but we can calculate the impact that violations of this assumption would have on our estimate of the ACME. As seen in Figure A5.1, if (per assumption) ρ=0, the ACME is positive and statistically significant; if ρ were about 0.27, the ACME would be zero. The literature does not offer any rules or conventions that would tell us whether the situation shown in the graph gives our estimate a sufficient margin of error (given that the actual ρ is unlikely to be *exactly* zero).

The software for preparing this graph (Hicks and Tingley 2010) would not accommodate dummy variable sets for either country or year; therefore, in this analysis we used data de-meaned by both country and year.

## Appendix 6 – Correlations

**Table 6.1 Correlation of variables, overall sample**

| | |
|---|---|
| N | 572 |
| Countries | 25 |
| Years | 1990-2013 |

| | Patents | UP | EP | R&D | Capital Stock | Education expenditure | Agriculture | Manufacturing | Services |
|---|---|---|---|---|---|---|---|---|---|
| Patents | 1.00 | | | | | | | | |
| UP | -0.56 | 1.00 | | | | | | | |
| EP | -0.10 | -0.23 | 1.00 | | | | | | |
| R&D | 0.93 | -0.77 | 0.06 | 1.00 | | | | | |
| Capital Stock | 0.83 | -0.88 | 0.20 | 0.96 | 1.00 | | | | |
| Education expenditure | 0.91 | -0.75 | 0.09 | 0.98 | 0.96 | 1.00 | | | |
| Agriculture | 0.11 | -0.28 | 0.29 | 0.22 | 0.28 | 0.21 | 1.00 | | |
| Manufacturing | 0.21 | 0.13 | 0.09 | 0.16 | 0.03 | 0.10 | 0.35 | 1.00 | |
| Services | -0.16 | 0.00 | -0.20 | -0.17 | -0.11 | -0.13 | -0.69 | -0.84 | 1.00 |

**Table 6.2 Correlation of variables, mediation sample**

| | |
|---|---|
| N | 442 |
| Countries | 23 |
| Years | 1994-2013 |

| | Patents | UP | EP | R&D | Capital Stock | Education expenditure | Agriculture | Manufacturing | Services | Diversity | Domestic |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Patents | 1.00 | | | | | | | | | | |
| UP | -0.51 | 1.00 | | | | | | | | | |
| EP | -0.04 | -0.34 | 1.00 | | | | | | | | |
| R&D | 0.94 | -0.72 | 0.14 | 1.00 | | | | | | | |
| Capital Stock | 0.83 | -0.86 | 0.26 | 0.95 | 1.00 | | | | | | |
| Education expenditure | 0.92 | -0.72 | 0.14 | 0.98 | 0.95 | 1.00 | | | | | |
| Agriculture | 0.14 | -0.27 | 0.21 | 0.20 | 0.27 | 0.20 | 1.00 | | | | |
| Manufacturing | 0.24 | 0.20 | 0.03 | 0.13 | -0.02 | 0.08 | 0.30 | 1.00 | | | |
| Services | -0.21 | -0.04 | -0.13 | -0.17 | -0.10 | -0.13 | -0.66 | -0.89 | 1.00 | | |
| Diversity | -0.49 | -0.12 | 0.27 | -0.32 | -0.17 | -0.35 | 0.34 | -0.18 | -0.02 | 1.00 | |
| Domestic immigration | -0.27 | -0.16 | 0.47 | -0.15 | -0.04 | -0.14 | 0.01 | -0.24 | 0.15 | 0.31 | 1.00 |