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Sunil Kanwar
Email: sunil_kanwar@econdse.org
Department of Economics,
Delhi School of Economics,
University of Delhi, India

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Delhi School of Economics
Delhi- 110007

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Sunil Kanwar
Delhi School of Economics

Abstract

Estimating a varying coefficients specification using an unbalanced panel of countries spanning the period 1997-2023, we find unambiguous support for the contention that educational attainment has a positive influence on innovation. The estimation results reveal that a one-year increase in mean years of education increases aggregate patent applications of a sample country by 1107, at the 50th percentile of the knowledge capital stock, or about 3.8% of the sample mean patent applications. Second, the innovation response to changes in education becomes stronger in the presence of larger stocks of knowledge capital. Thus, at the 95th percentile of the knowledge capital stock, we find that a one-year increase in the education level raises aggregate patent applications by 1264, or about 4.4% of the sample mean patent applications. This response to a unit-increase in the treatment variable is about 14.2% larger than what we found at the 50th percentile of the stock of knowledge capital, exemplifying the strengthening response at higher levels of the knowledge capital stock. Third, we find that the overall innovation-education response does not hinge upon any individual sector, but rather obtains across all the technology-intensive industry groups, namely, Chemicals, Electricals and Electronics, Machinery (non-electrical), Pharmaceuticals, and Professional and Scientific Equipment. Our results are robust to a number of sensitivity checks.

Keywords: Innovation, Education, Heterogeneity, Technology groups

JEL codes: O34, O38, O43

1. Motivating the Issue

The age of serendipitous innovation and of harvesting the low-hanging fruit appears to be long over. Innovation today is a more laborious process requiring higher levels of education than in earlier times. Scholars argue that while physical capital can be transferred easily over space and time, that is not true of human capital, because the repository of human capital, the individual, must acquire that knowledge in the first place (Jones 2009). Typically, this acquisition is at least partially and increasingly via formal education.[1] Education not only equips individuals with

[1] For this reason, Baumol (2005) cautions that the fact that colossi such as Thomas Edison, Robert Fulton, Samuel Morse, James Watt, Eli Whitney, and the Wright brothers Orville and Wilbur lacked formal education, may not be of relevance for understanding the innovation-education nexus in our present context.

technological capability and analytical tools to participate in innovation activities, but also stimulates creativity and imagination, and facilitates their application.

Despite its perceived importance for innovation, there is scant evidence on the education-innovation relationship in the literature. Instead, one finds studies pertaining to the relationship between education and economic growth. While certainly relevant, these studies cannot deflect the criticism that education may influence diverse factors other than innovation that, in turn, influence economic growth. By implication, the claim that education contributes to innovation activity is one that needs to be independently established.

The formalisation of the idea that education plays a significant role in the process of economic growth can be traced to the models of endogenous growth. The early endogenous growth models introduced human capital with spillover effects,[2] thereby eliminating diminishing returns to capital, which meant that human capital accumulation (importantly, education) could increase growth indefinitely. Later research explored the lure of monopoly profits motivating innovation as the modus operandi to overcome diminishing returns in the long run,[3] which again implies the importance of education in generating new ideas for economic growth.

The empirical growth literature supports the theoretical growth literature in underlining the importance of education. Several studies show that countries with more human capital grow faster,[4] with one study[5] even arguing that human capital (measured 'differently' from other studies) indeed explains *all* observed cross-country income differences. Replacing education-based human

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[2] See Romer (1986), Lucas (1988), and Rebelo (1991).
[3] See Aghion and Durlauf (2009), Romer (1990), Aghion and Howitt (1992), and Grossman and Helpman (1991).
[4] See Manuelli and Seshadri (2014), Bils and Klenow (2000), Benhabib and Spiegel (1994), and Mankiw, Romer, and Weill (1992).
[5] Jones (2014).

capital measures by cognitive skill-based measures, another strand of the literature demonstrates that countries with higher cognitive skills grow faster.[6]

While the economic growth literature places much importance upon human capital, it does not provide direct evidence on the education-innovation nexus per se. For that, we must turn to other studies. In a very interesting study, Bianchi and Giorcelli (2020) use Italian data to reveal that 64% of the inventors had an industrial diploma vis-à-vis 35% of the non-inventors, that inventors displayed higher academic ability with a high school grade 0.26 standard deviations above-mean, and that inventors were more likely to attend university for a science, technology, engineering, and mathematics (STEM) degree. They go on to demonstrate, that wider access to STEM education in 1960 Italy led to increased patenting. Andrews (2019) reports that agricultural patents and new crop varieties increased in the US counties that benefited from land grant colleges, relative to the 'control counties' which did not so benefit. Valero and Van Reenen (2019) find that the establishment of universities in countries across the globe appears to have increased innovation in those locations over 1950-2010. Toivanen and Vaananen (2016) report that greater access to master-level engineering programmes in Finland substantially raised patenting. Rodriguez-Pose (1999) demonstrates that a major difference between innovation-receptive and innovation-resistant regions in Europe was the availability of skills.

We contribute to this interesting literature in several ways. First, our paper is amongst the very few to specifically study how variations in educational attainment influence innovation outcomes. Instead of focusing on a single nation or industry, our results permit a more generalisable contention that more educated nations exhibit greater innovation. Second, we study the possibility that the innovation response to educational attainment likely varies across nations

[6] Hanushek and Woessmann (2010).

and time, being larger at larger stocks of knowledge capital. Third, we study whether this relationship is uniform or heterogeneous across technology-intensive industry groups.

Estimating a varying coefficients specification using an unbalanced panel of countries spanning the period 1997-2023, we find unambiguous support for the contention that educational attainment has a positive influence on innovation. The estimation results reveal that a one-year increase in mean years of education increases aggregate patent applications of a sample country by 1107, at the 50th percentile of the knowledge capital stock, or about 3.8% of the sample mean patent applications. Second, the innovation response to changes in education becomes stronger in the presence of larger stocks of knowledge capital. Thus, at the 95th percentile of the knowledge capital stock, we find that a one-year increase in the education level raises aggregate patent applications by 1264, or about 4.4% of the sample mean patent applications. This response to a unit-increase in the treatment variable is about 14.2% larger than what we found at the 50th percentile of the stock of knowledge capital, exemplifying the strengthening response at higher levels of the knowledge capital stock. Third, we find that the overall innovation-education response does not hinge upon any individual sector, but rather obtains across all the technology-intensive industry groups, namely, Chemicals, Electricals and Electronics, Machinery (non-electrical), Pharmaceuticals, and Professional and Scientific Equipment. Our results are robust to a number of sensitivity checks.

Section 2 sets out the modelling strategy, and derives the specification to be estimated. Section 3 discusses the model variables, and the dataset employed in estimation. Section 4 reports and interprets the empirical results, along with the robustness checks, and Section 5 provides some brief conclusions.

2. The Model Specification

Extending Pakes and Griliches (1984), we hypothesize that the level of technological knowledge or innovation in country i at time t (INN_{it}), is given by a knowledge production function with inputs human capital ($HUMK_{it}$) and knowledge capital stock ($KNOWK_{it}$), controlling for other relevant factors (C_{it}). That is,

$$INN_{it} = G_{it}(HUMK_{it}, KNOWK_{it}, C_{it}) + u_{it} \tag{1}$$

where u captures the inherent randomness of knowledge production.

While referring to human capital, we shall focus on its most salient component, education (EDU). The specific pathways via which education likely influences innovation are complex. Some argue that education nurtures cognitive and noncognitive skills, which increase the productivity of potential innovators (Biasi et al. 2022). While innate traits may distinguish inventors from non-inventors (Aghion et al. 2017), education may still play a significant role in determining how successfully these traits translate into innovation. Thus, there is evidence that education improves cognitive ability: with each additional school year raising the intelligence quotient (IQ) by 1 to 5 points in a meta-analysis of numerous datasets (Ritchie and Tucker-Drob 2018), an additional school year raising the intelligence scores of Swedish school children by 0.01 standard deviations (Carlsson et al. 2015), with access to special (gifted and talented) school programmes raising the math scores of US Black students by 0.7 standard deviations (Card and Giuliano 2016), and an additional school year raising the cognitive skills of US racial minorities in later life (Cascio and Lewis 2006).

Likewise, evidence shows that education may also be instrumental in enhancing the noncognitive skills of children. Empirical evidence for England shows that pre-school education has a positive effect on the noncognitive skills of boys, which persists even at age eleven

(Cornelissen and Dustmann 2019). Other evidence shows that work-based education (i.e., vocational education and training, with apprenticeships) increased the emotion-centred stability of a sample of Swiss children, as compared to the control group which received only school-based education (Bolli and Hof 2018). Taken together, the above-mentioned evidence implies that education could help 'create' innovators by enhancing the cognitive and noncognitive skills of individuals, and thereby increase innovation in society. A corollary of this conclusion is, that education also improves the ability to build upon technology developed elsewhere (Teixeira and Fortuna 2010; Leiponen 2005; Lee 2001). For completeness, we also note the contrary possibility, that in some situations, education may hinder creativity (Baumol 2005) insofar as it leads individuals to think in a prosaic manner, and eschew unorthodox techniques that often underpin breakthrough innovations. Baumol (2005) opines that society requires both breakthrough and cumulative improvements, with the sum total of the latter historically dominating the former.

We represent innovation (INN_{it}) by patents per capita (PAT_PC_{it}),[7] recognizing that patents are an imperfect proxy for the level of technological knowledge in a country (Griliches 1990; Madsen 2007). The patent production function (Pakes and Griliches 1984; Hall et al. 1986; Cincera 1997; Blundell et al. 2002) is then

$$PAT\_PC_{it} = g_{it}(EDU_{it}, KNOWK_{it}) + \gamma C_{it} + \lambda_i + \theta_t + u_{it} \tag{2}$$

where the systematic impact of education, knowledge capital stock and the confounders has been additively separated from the country fixed effects λ_i, the year fixed effects θ_t, and the idiosyncratic errors u_{it}.

In exploring the average treatment effect of variable EDU, we allow for the possibility that education has a heterogeneous effect across countries and time. One way of doing this is to model

[7] Patents per capita would be a more appropriate measure than patents per se, when comparing across countries and over time.

β_{it} via a varying coefficients specification (Sperlich and Theler 2015; Frölich and Sperlich 2019), wherein β_{it} is a function of the extent to which countries might benefit from human capital. To allow for this possibility, we express β_{it} as the linear function $\beta(.) = \beta * (a + b * KNOWK_{it})$, which implies that the larger the research and development (R&D) investment or the knowledge capital stock in a country, the more it would benefit from its human capital, since the larger knowledge capital would boost the productivity of its human capital in generating innovation. Using this approximation, specification (2) becomes:

$$PAT\_PC_{it} = \beta_1 EDU_{it} + \beta_2 KNOWK_{it} * EDU_{it} + \gamma C_{it} + \lambda_i + \theta_t + u_{it} \quad (3)$$

which would yield the average treatment effect of variable EDU on variable PAT_PC, given the value of $KNOWK$.

Some may assert the possibility of reverse causality, such that $Cov(EDU_{it}, u_{it}) \neq 0$. We deal with this possibility by employing the control function method (Imbens and Wooldridge 2007; Blundell and Powel 2003; Heckman 1976). We first regress variable EDU_{it} on instrument(s) I_{it}, controlling for the confounders C_{it}, and compute residuals $\hat{\eta}_{it}$. These residuals capture the influence of all omitted variables on EDU_{it}, including that of the dependent variable PAT_PC_{it}, if there is any.[8] Equation (3) may then be re-written as:

$$PAT\_PC_{it} = \beta_1 EDU_{it} + \beta_2 KNOWK_{it} * EDU_{it} + \gamma C_{it} + \delta\hat{\eta}_{it} + \lambda_i + \theta_t + \epsilon_{it} \quad (4)$$

Given that $\hat{\eta}_{it}$ captures the reverse causal effect of PAT_PC on EDU, the error term in (4) is no longer plagued by this previously omitted variable, so that $\epsilon_{it} \perp (EDU_{it}, \hat{\eta}_{it})$, allowing us to obtain the coefficient estimates of interest from the above equation.[9]

[8] The control function approach is preferable to the two-stage least squares technique, because it retains the original causal variable(s) in the estimation equation (Imbens and Wooldridge 2007), and it is more efficient when the relationship estimated is nonlinear (Guo and Small 2016).

[9] Needless to say, an insignificant δ would imply an insignificant reverse causal effect.

3. Sample Dataset and Model Variables

Having motivated our causal model relating innovation in a country to its educational attainment, we now consider the data at our disposal. Since R&D data (which underlie the knowledge capital variable) are available only from 1996 to 2023, our sample period is restricted to 1997-2023, since we require lagged R&D to construct the knowledge capital stock, as detailed below in section 3.3. Dropping the records for which no data are available for the other regressors in our causal model of equation (5), we are left with an unbalanced panel of 1284 observations spanning the period 1997-2023 across 57 countries (listed in Appendix 1).[10]

3.1 The Dependent Variable

For the aggregate economy-wide analysis, we define the regressand as patent applications per capita (PAT_PC), where these applications are made by the residents of a country, or those for which the first applicant is a resident of the country in question (WIPO 2026). These applications are filed worldwide via the Patent Cooperation Treaty channel or else the national patent office, and the application year is the filing year.

Of course, patents are imperfect indicators of innovation. Some firms do not take out patents (Levin et al. 1987) to avoid disclosure. Small firms eschew patents since they are costly to acquire and protect (Mohnen 2019), which becomes more relevant for innovations not regarded valuable enough. Some firms shun patents, because natural barriers to entry (such as production scale, complexity of technology, etc.) suffice for profit appropriation (Cohen, Nelson and Walsh

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[10] We were forced to drop a very small number of records on account of missing data for the patent variables. Note that these missing data do not imply zero values. For example, although patent applications data for Ireland are missing for some years before 2016, there were 755 applications in 2016! The missing data appear to be the result of changing application protocol, as my correspondence with the Intellectual Property Office of Ireland confirmed (<Fergal.Brady@ipoi.gov.ie>). Moreover, these data constitute a mere 0.2% to 2.2% of the remaining sample size of 1284.

2000). We also recognize, that patent-related innovation indicators may be inappropriate in some contexts, given that technology-intensive industries patent heavily in comparison to nontechnology-intensive industries (Cohen, Nelson and Walsh 2000; Maskus 2000). Further, patent-related innovation indicators may be ill-suited in some situations if innovations are mostly 'new to the world' in some (rich) countries, but mostly 'new to the firm' in some (poor) countries (Crescenzi and Jaax 2017). While patent citations may assist in gauging the direction and intensity of knowledge flows across countries (Peri 2005), country-specific citation data are not currently available. Despite these caveats, there is broad agreement that patent-related measures are very useful indicators of innovation (Griliches 1990; Madsen 2007).

3.2 The Treatment Variable: Educational Attainment

The 'treatment variable' in this analysis is educational attainment (EDU), which we capture in terms of the number of years of education in the population aged 15-plus. Combining the Barro and Lee five-yearly data till 2010 (Barro and Lee 2013), the last year for which they are available, and their five-yearly projections for the post-2010 period (Barro and Lee 2015), we compute the annual data series for this variable on the premise of proportionate change between any two five-yearly endpoints. We appreciate that in the innovation context, other variables such as the percentage population with STEM degrees may be more appropriate, but such data are not available for any substantial time series for a large enough sample of countries.

3.3 Control Variables

It is well-recognized that research and development investment is vital for innovation (Baumann and Kritikos 2016, Bogliacino and Pianta 2013, Mairesse and Mohnen 2005; see also Audretsch and Belitski 2020). Instead of using R&D investment flows, however, this input is better captured by the stock of knowledge capital resulting from these flows, since that allows for knowledge accumulation. The R&D flows data (World Bank 2026a) comprise capital and current expenditures on basic research, applied research, and development, in the business enterprise, government, higher education and private non-profit sectors. We compute the knowledge capital stock via the perpetual inventory equation $KNOWK_t = (1 - \phi)KNOWK_{(t-1)} + RD_t$, where RD denotes research and development expenditure, ϕ represents the depreciation rate of knowledge capital, and t indicates the time period (Hall 1990, Kanwar and Hall 2017).[11]

Government efficiency may support or hinder innovation. Although it is possible to nurture an efficient bureaucracy (Weber 1968) which may boost innovation, weak monetary incentives, excessive job security, scant internal competition (Côté 2012; Teodoro 2009), lack of an appropriate value system (Dougherty and Corse 1995), and excessive self-interest (Dixit 2012) may render it inefficient, hindering innovation. We define governance efficiency (GOV) as the average of the 'size of government' and 'regulation' sub-indices from the Economic Freedom dataset (Gwartney, Lawson, and Murphy 2025). This index ranges between 0 and 10, with larger values signifying superior governance.

Technology licensing may aid domestic innovation (Kanwar 2012), and has been of increasing importance lately (Mowery and Oxley 1995). Thus, inward-licensing improved domestic technology development in a sample of Chinese firms (Li-Ying and Wang 2015), as also firms in the global pharmaceutical industry (Moreira et al. 2020), and also increased innovation complexity (Wang et al. 2015). We represent technology licensing by payments made by one

[11] To derive the value of the knowledge capital stock in the 'first' period, we divide the R&D investment in that period by the sum of the depreciation rate of knowledge capital δ (taken as 15% p.a. following Hall 1990) and the pre-sample growth rate of R&D (proxied by the growth rate of R&D over roughly 1996-2023).

country to other countries for using their intellectual property such as patents, industrial designs, layout designs of integrated circuits, trademarks, service marks, and copyrights, as well as franchises, as a proportion of the payer's gross domestic product, and we denote this variable $TECH\_LIC$ (World Bank 2026a).[12]

Another potential channel of international technology spillover is foreign direct investment inflows, although the empirical evidence is mixed in this regard. While several earlier studies do not support the contention that technology inflows likely piggy-back on foreign direct investment (Primo Braga and Fink 1997, Kondo 1995, Maskus and Eby-Konan 1994, Ferrantino 1993, Mansfield 1993), some more recent studies are indeed consistent with this contention (Kanwar and Sperlich 2023, Awokuse and Yin 2009, Javorcik 2004, Park and Lippoldt 2003). We represent this factor by the foreign direct investment inflows into a country as a ratio of its gross domestic product (FDI_INF).

International technology spillovers may also contribute to domestic innovation (Madsen 2007; Connolly 2003; Coe and Helpman 1995). High-tech commodity imports[13] may serve as inputs into technological processes, or be the object of reverse engineering (Keller 2010). Similarly, low-tech commodity imports may be relevant for countries lower down the skill and education spectrum. Evidence shows higher productivity in a sample of Indonesian downstream firms that benefited from import-intensive inputs from upstream firms (Blalock and Veloso 2007), as well as in a sample of Chilean plants following an episode of import liberalization (Pavcnik

[12] We recognise that payments for trademarks and copyrights may not be associated with technology transfer, and that firms may indulge in transfer pricing for technology transferred between multinational parent and subsidiaries, but data constraints prevent any rectification.

[13] These are defined as products from the aerospace, armaments, chemicals, computers and office machines, electrical machinery, electronics and telecommunications, non-electrical machinery, pharmaceuticals, and scientific instruments industries (SITC Revision 4).

2002).[14] Exports may induce domestic firms to become more innovative when faced with high international competition, but induce lagging firms to become less innovative when faced with low international competition (Smith 2014).[15] We represent this gamut of factors by a country's trade in goods and services (imports plus exports) as a ratio of its gross domestic product ($TRADE$).[16]

The strength of intellectual property protection that a nation provides may be another factor driving its domestic innovation (Branstetter, Fisman and Foley 2006; Chen and Puttitanum 2005). Evidence also shows that intellectual property rights influence the location and nature of technology development across countries (Lamin and Ramos 2016; Zhao 2006). Of course, this relationship may be non-linear given the high costs of innovation, and evidence shows that both very weak and very strong IPRs discourage innovation, implying that moderate protection may be ideal (Furukawa 2010). Studies also show that the enforcement aspect of IPRs matters for innovation (Papageorgiadis and Sharma 2016). We represent intellectual property protection by the modified Ginarte-Park index of patent rights. The original index (Ginarte and Park 1997; Park 2008; Kazakou and Park 2023) summarises five sub-indices pertaining to patent protection – subject matter, length, membership of international bodies, provisions preventing revocation once granted, and enforcement provisions, with each sub-index ranging from 0 to 1, and their simple mean constituting the Ginarte-Park index. Taking advantage of the stable and steady increase in this index over time, we annualize the five-yearly series assuming proportional change in the intervening years. To convert this de jure index into a de facto measure, we use the 'legal system

[14] We realise that in addition to spillovers, a country's imports can have a more complex effect on its domestic innovation. Imports may result in downward pressure on prices and profits, inducing the survivor domestic firms to either become more innovative (Bloom et al. 2016, Keller 2002, Bernstein and Mohnen 1998, Coe and Helpman 1995), or less innovative (Autor et al. 2020).

[15] For surveys of the trade-innovation nexus see Shu and Steinwender (2018), and Akcigit and Melitz (2022).

[16] Some technology transfer may also occur via movement of personnel, but data constraints do not permit us to account for that factor.

and property rights sub-index'[17] from Gwartney, Lawson and Murphy (2025). Adjusting its range to 0-1, we add it to the annualized Ginarte-Park series, to derive the intellectual property protection variable (IPP), which ranges from 0 to 6, with larger values reflecting stronger protection.

3.4 Computing the control function variable

We now discuss the computation of the control function variable $\hat{\eta}_{it}$ in equation (4). For this purpose, we use 'parental' educational attainment as an instrument for current educational attainment. Although this is not literally possible given that we do not have individual-specific data, we can still use the educational attainment lagged 'one generation' or say 30 years ($EDU30$), as an instrument for current period educational attainment (EDU), consistent with research on generation length (Wang et al. 2023; Fenner 2005). Since our sample period is 1997-2023, we define $EDU30$ as education relating to the period 1967-1993. In this manner, 1967 education instruments the 1997 education, 1968 education instruments the 1998 education, and so on.

Since a quadratic regression provides a better fit to our EDU data, regressing EDU_{it} on instruments $EDU30_{it}$ and $EDU30_{it}^2$, conditioned on the confounders C_{it} and the country and year fixed effects, we derive the residuals $\hat{\eta}_{it}$.Note that the average years of education of the 'parental generation' $EDU30$ influences the outcome variable PAT_PC via the treatment variable EDU. We find that $Corr(EDU, EDU30) = 0.8872$, and $Corr(EDU, EDU30^2) = 0.8392$ for our sample. Further, $Corr(EDU30, \hat{u}_{it}) = 0.0124$, and $Corr(EDU30^2, \hat{u}_{it}) = -0.0122$, where $\hat{u}_{it}$ are the

[17] This sub-index is based on data pertaining to the protection of property rights, judicial independence, impartiality of courts, integrity of the legal system, legal enforcement of contracts, regulatory costs of the sale of physical property, reliability of police, business costs of crime, and military interference in the rule of law and politics.

residuals from equation (3). For these reasons, $EDU30$ and $EDU30^2$ are valid instruments for the treatment variable EDU.[18]

Employing $\hat{\eta}_{it}$ from the first stage regression as an additional regressor, and using the logarithm of PAT_PC ($LPAT\_PC$) and the logarithm of $KNOWK$ ($LKNOWK$) because the original variables are highly skewed, we obtain our final estimation equation:

$$LPAT\_PC_{it} = \beta_1 EDU_{it} + \beta_2 LKNOWK_{it} * EDU_{it} + \gamma_1 GOV_{it} + \gamma_2 TECH\_LIC_{it} + \gamma_3 FDI\_INF_{it} + \gamma_4 TRADE_{it} + \gamma_5 IPP_{it} + \delta\hat{\eta}_{it} + \lambda_i + \theta_t + \epsilon_{it} \quad (5)$$

where the model variables have been defined above (as well as in Appendix 2), λ_i are the country fixed effects (representing unobserved heterogeneity on account of difficult to measure factors such as research ethos, scientific temperament, attitudes towards work, etc.), θ_t are the year fixed effects (controlling for factors such as the international economic shock of 2008, the Covid shock of 2020, investment environment, etc.), and ϵ_{it} is the idiosyncratic error term.

4. Empirical Results

We begin by discussing the empirical results from the estimation of equation (5), and then go on to present a number of robustness checks.

4.1 Aggregate innovation response: The baseline model

The 'baseline' results from the estimation of equation (5) are reported in column (1) of Table 2. The strong significance of educational attainment in explaining variations in patents per capita is borne out by the fact that variables EDU and $LKNOWK * EDU$ are jointly strongly significant, as

[18] The *F*-statistic for the test that the instruments are 0 in this first stage regression is 9.84, and the *J*-statistic for the test of overidentifying restrictions following the second stage estimation of equation (5) is 0.2820, with a p-value of 0.5954.

reflected by the p-value of 0.0085 provided at the bottom of column (1). Further, education not only has a strongly significant main effect on the regressand, with variable EDU significant at the 1% level, this effect is heterogeneous and increases with the level of the knowledge capital stock as evidenced by the strong significance of the interaction term $LKNOWK * EDU$ at the 5% level. The estimated coefficients of variables EDU and $LKNOWK * EDU$ indicate, that a one-unit improvement in educational attainment EDU increases the number of patent applications of a sample country by about 1107, at the 50th percentile of the knowledge capital stock variable $LKNOWK$. This is about 3.8% of the sample mean of total patent applications. At the 95th percentile of the knowledge capital stock, a one-unit increase in education raises patent applications by 1264 or about 4.4% of the sample mean patent applications. Thus, at the 95th percentile of the knowledge capital stock compared to the 50th percentile, the effect of a unit increase in education on innovation is about 14.2% higher.

Amongst the confounder variables, the inflow of technology via technology licensing $TECH\_LIC$ has a strong positive effect on the dependent variable, significant at the 1% level, while the governance variable GOV has a weak positive association with innovation, significant at the 10% level. In addition, the intellectual property protection variable IPP is mildly positively significant, using a one-tail test at the 10% level. The insignificance of FDI and $TRADE$ in explaining variations in innovation is consistent with Lall (2003), who demonstrates that countries conducting more innovation are not necessarily beneficiaries of foreign investment. Finally, the control function variable $\hat{\eta}$ is strongly significant, justifying the equation (5) specification in correcting for the possibility of reverse causality.

4.1.1 ***Innovation response by technology group***

The patent response to education that we studied in the previous section was at the aggregate level, where the patents in question straddle several different technology categories. It would be useful to enquire if the significance of education for innovation holds homogeneously across numerous technology groups or whether it is heterogeneous. To study this question, using the World Intellectual Property Organisation's technology classification (WIPO 2026; Schmoch 2008), we identify five groups of industries which are technology-intensive, and for which patents appear to be a significant instrument of surplus appropriation (Cohen, Nelson and Walsh 2000). These are: Group 1 – Electrical and Electronics Technology, Group 2 – Professional and Scientific Equipment, Group 3 – Pharmaceuticals, Group 4 – Chemicals, and Group 5 – Non-electrical Machinery (see Appendix 3 for the detailed composition of each category). Normalising the patent publications for each of these industry categories by population and taking logs, we obtain the dependent variables for the dis-aggregated analysis – namely, $LPAT\_PC\_GP1$, $LPAT\_PC\_GP2$, $LPAT\_PC\_GP3$, $LPAT\_PC\_GP4$, and $LPAT\_PC\_GP5$.

Re-estimating equation (5) using each of these dependent variables in turn, we derive the empirical results that are presented in column (2) through column (6) of Table 2. In each regression, variables EDU and $LKNOWK * EDU$ are jointly strongly significant at around the 1% level or less, as indicated by the p-values at the bottom of columns (2) to (6), implying the strong significance of education for innovation. Once again, in addition to the strongly significant main effect of variable EDU on the regressand, this effect increases with the level of the knowledge capital stock insofar as the interaction term $LKNOWK * EDU$ is also strongly significant at the 5% level or less. The coefficients of variables EDU and $LKNOWK * EDU$ imply that a one-unit increase in the educational variable EDU would likely increase the patent publications by about

298 for group 1, 237 for group 2, 91 for group 3, 274 for group 4, and 135 for group 5 industries, at the 50th percentile of the knowledge capital stock variable $LKNOWK$. These increases translate to about 2.4%, 4.1%, 6.1%, 5.3%, and 4.4% of the sample mean patent publications for the respective categories. As in the aggregate analysis, these category-specific responses increase with the level of the knowledge capital stock. For instance, at the 95th percentile of the knowledge capital stock, a one-unit increase in the education variable increases patent publications by 346 for group 1, by 288 for group 2, by 115 for group 3, by 328 for group 4, and by 171 for group 5. These increases translate to about 2.8%, 4.9%, 7.7%, 6.4%, and 5.5% of the sample mean patent publications of the five groups, respectively. Alternatively stated, at the 95th percentile of the knowledge capital stock in comparison to the 50th percentile, the effect of a unit increase in the education variable EDU on patent publications is larger by roughly 16% for group 1, 21% for group 2, 26% for group 3, 20% for group 4, and 27% for group 5 industries.

Amongst the control variables, technology licensing $TECH\_LIC$ is strongly positively associated with the regressand in all five group regressions. The governance variable GOV also exhibits a positive association with innovation, varying from weak to strong significance in four of the five regressions (Kanwar 2025). Foreign direct investment inflows FDI_INF are strongly positively significant in four of the five regressions, being insignificant for just group 1 industries. The intellectual property protection variable IPP has a mildly to strongly significant positive effect on the dependent variable in four of the five regressions. The importance of $TRADE$ vis-à-vis innovation appears to vary across technology groups, being strongly significant for group 1 and weakly so for group 2 industries, though insignificant for the other groups. Intellectual property protection has a positive association with innovation in four of the five regressions, though this varies from weakly to strongly significant. Finally, the control function variable $\hat{\eta}$ is strongly significant for only the group 4 regression, and is weakly significant in the other cases, justifying nevertheless our use of the equation (5) specification in correcting for the possibility of reverse causality. Evidently, the baseline dis-aggregated group-specific results are in broad conformity with the aggregate baseline results.

4.2 Robustness check: Alternative generation length

In our first robustness check, to compute the control function variable $\hat{\eta}_{it}$ in equation (5), we take the generation length to be 25 years rather than 30 years (Wang et al. 2023; Fenner 2005). The 'basic' instrumental variable then becomes educational attainment lagged 25 years ($EDU25$). Given our sample period of 1997-2023, $EDU25$ is defined over the period 1972-1998, such that the 1972 education level instruments the 1997 education level, the 1973 education level instruments the 1998 education level, and so on. In line with the first stage specification used in the baseline exercise, we regress EDU_{it} on instruments $EDU25_{it}$ and $EDU25_{it}^2$, conditioned on the confounders and the country and year fixed effects, to derive variable $\hat{\eta}_{it}$. Data reveal that $Corr(EDU,\ EDU25) = 0.8985$, and $Corr(EDU,\ EDU25^2) = 0.8609$ for our sample. Further, $Corr(EDU25, \hat{u}_{it}) = 0.0102$, and $Corr(EDU25^2, \hat{u}_{it}) = -0.0094$, validating our instruments.

Using the re-computed $\hat{\eta}_{it}$ from the first stage regression as an additional regressor, we re-estimate equation (5), first with $LPAT\_PC$ as the dependent variable, and then with the group-specific regressands $LPAT\_PC\_GPj$, where $j = 1, \ldots, 5$. These regression estimates are reported in Table 3.

It is evident that the estimates are consistent with the baseline results reported in Table 2. Both for the aggregate results in column (1), as well as for the dis-aggregated technology group-wise results in columns (2) to (6), the education variable EDU has a strong association with innovation, with the p-values at the bottom of the table indicating significance mostly at less than the 1% level. Not only does this variable exhibit a strongly significant main effect, with EDU being significant at the 5% level or less in five of the six regressions and weakly so in the sixth, this effect strengthens with the level of the knowledge capital stock, with the interaction term $LKNOWK * EDU$ also being significant at the 5% level or less in five of the six regressions and weakly so in the sixth. In view of the conformity of these results with the baseline results of Table 2, we consider it unwarranted to re-estimate the expected increase in patents (in the aggregate and for each of the five technology groups) for a unit increase in EDU, and to show that this response is larger at higher levels of the knowledge capital stock.

The results pertaining to the control variables are also more or less in line with those of the baseline regressions of Table 2. The technology licensing variable $TECH\_LIC$ has a strong positive effect on the dependent variable, significant at the 1% level, while foreign direct investment inflows FDI_INF are strongly positively significant in four of the six regressions. The governance variable GOV, and intellectual property protection IPP, both have a positive association with innovation, which varies in significance from weak to strong across five of the six regressions. The $TRADE$ variable in mostly insignificant in explaining innovation, consistent with Lall (2003). Finally, the weak to strong significance of the control function variable $\hat{\eta}$ in five of the six cases justifies the use of specification (5) in correcting for possible reverse causality.

4.3 Robustness check: Alternative governance indicator

We now use the Worldwide Governance Index (World Bank 2026b; Kaufmann and Kraay 2024), in place of the governance index used in the baseline regressions, and label it $GOV2$. It is computed as the average of six sub-indices pertaining to various dimensions of governance – namely, ‘voice and accountability', 'political stability and absence of violence/terrorism', 'government effectiveness', 'regulatory quality', 'rule of law' and 'control of corruption'. Although the original index ranges between –2.5 and +2.5, we rescale it to range from 0 to 100, with larger values signifying superior bureaucratic performance.[19] Re-estimating equation (5) for the aggregate and group-wise patents per capita dependent variables, we derive the regression results reported in Table 4.

It is apparent that the estimates agree with the baseline results of Table 2. The aggregate results in column (1), and the group-wise results in columns (2) to (6), all indicate that education has a strong association with innovation, with the p-values at the bottom of Table 4 supporting the joint significance of EDU and $LKNOWK * EDU$ at less than the 1% level. Variable EDU has a strongly positive main effect on the dependent variable, significant at the 5% level or less, and this effect increases with the knowledge capital stock, the interaction term $LKNOWK * EDU$ being significant at the 5% level or less in five of the six regressions and weakly so in the sixth. The results for the confounders are similarly in line with those in the baseline regression, and need not be repeated here. In view of these similarities, we eschew re-estimation of the semi-elasticities of patents per capita (in the aggregate and disaggregated by technology group) for a unit change in the education variable EDU.

4.4 Robustness check: Alternative trade measure

In this exercise, we re-define the trade measure in terms of sub-index 4 of the Economic Freedom data (Gwartney, Lawson, Murphy 2025), which encompasses tariff barriers, nontariff trade barriers, black market exchange rate premia, and capital and labour market controls, Re-estimating

[19] The re-scaling is done using the relationship GOV2 = 50 + 20*WGI, where WGI is the original world governance index and GOV2 is the re-scaled index.

equation (5) using this measure $TRADE2$ yields the results presented in Table 5, which evidently match the baseline results of Table 2. Variables EDU and $LKNOWK * EDU$ are jointly strongly significant at around the 1% level or less, suggesting a strong association between innovation and education. Not only is the main effect of variable EDU strongly significant in all cases, it increases with the level of the knowledge capital stock, the interaction term being strongly significant at the 5% level or less in four of the six cases, and weakly so at the 10% level in the other two. Amongst the confounders, technology licensing ($TECH\_LIC$) remains strongly significant in all cases, foreign direct investment inflow (FDI_INF) displays strong significance in four of the six cases, and the governance (GOV) and intellectual property protection (IPP) variables display statistical significance ranging from strong to weak across five of the six regressions, mostly agreeing with the original results of Table 2.

4.5 Robustness check: Larger weight on implementation component of IPR index

To validate our results further, we now re-define the intellectual property protection variable by placing twice the weight on the implementation component (i.e., the 'Area-2' sub-index). Re-estimation of equation (5) with this redefined index $IPP2$ yields the results reported in Table 6. The aggregate results in column (1) and the group-wise results in columns (2) to (6) all conform with the baseline results in Table 2. The hypothesis that EDU and $LKNOWK * EDU$ are jointly insignificant is strongly rejected at around the 1% level or less in all cases, implying a strong association between innovation and education. This response becomes larger at higher levels of the knowledge capital stock, as indicated by the strong significance of the interaction term at the 5% level or less. Amongst the control variables, technology licensing ($TECH\_LIC$), governance

(GOV), foreign direct investment inflow (FDI_INF), and intellectual property protection (IPP) display strong to weak significance across the regressions, in keeping with the baseline results.

4.6 Robustness check: Alternative specification

As our last robustness check, we include the knowledge capital stock variable $LKNOWK$ as an additional regressor in equation (5). From the estimation results in Table 7, it is evident that this variable is strongly insignificant in the aggregate results in column (1), as well as in four of the five group-specific results, justifying its omission from our baseline specification. The strong significance of education for innovation still holds, as is evident from the *p*-values of the test of joint insignificance of variables EDU and $LKNOWK * EDU$ provided at the bottom of Table 7. Further, the main effect of variable EDU on the regressand remains strongly significant in all six regressions, at the 5% level or less, and this effect strengthens at higher levels of the knowledge capital stock in five of the six regressions, as is evident from the semi-elasticities reported at the bottom of the table. Finally, the results vis-à-vis the confounders are also more or less in sync with those of the original specification that omits regressor $LKNOWK$. Therefore, it is preferable to revert to our original specification.

5. Conclusions

In this paper we study the innovation-education nexus, a prominent facet of the process of modern economic growth. Innovation, for some time now, has been a deliberate, relatively laborious process, requiring higher levels of formal education than historically. It is well-recognised that education equips individuals with technological capability and analytical tools to participate in the innovation process, and stimulates creativity and imagination while facilitating their application. Evidently, under-provisioning for education is likely to retard innovation.

Employing data for a panel of nation states for the period 1997-2023, we find strong evidence that higher educational attainment underscores superior innovation outcomes. A one year increase in mean years of education increases aggregate patent applications by about 1107, at the sample median stock of knowledge capital. This response is heterogeneous, and is higher at higher levels of a country's knowledge capital stock. For instance, the increase in total patent applications for a unit increase in mean years of education is about 1264 at the 95th percentile of the sample knowledge capital stock, which is a substantial 14.2% larger than that at the 50th percentile stock.[20] Additionally, this response of patent production to educational attainment does not appear to be limited to any single industry group, but rather obtains for all five technology-intensive industry groups. Our results remain consistent in the face of a number of robustness checks. Ceteris paribus, therefore, the benefits of raising educational attainment for a country's innovation appear to be substantial.

[20] Employing the coefficient estimates from Table 2, we can make some rough conjectures about the high-income versus medium-income countries in our sample. A one-unit increase in mean years of education in a high-income country would increase total patent applications in that country by 1356 (or 5.4% of the mean patent applications in those countries) at the 50th percentile of the knowledge capital stock for this group, and by 1626 (or 6.5% of the mean patent applications) at the 95th percentile of the knowledge capital stock of this group. This implies that the marginal effect of educational improvement on innovation is about 19.9% larger at the 95th percentile of the knowledge capital stock compared to the 50th percentile, in high-income countries. In similar manner, a unit increase in mean years of education in a medium-income country would increase total patent applications of the country by only 697 (or 1.9% of the mean patent applications of that group) at the median knowledge capital stock of medium-income countries, and by 777 (or 2.1% of the mean patent applications of that group) at the 95th percentile of the knowledge capital stock of that group. Thus, the marginal effect of educational improvement on innovation is about 11.5% larger at the 95th percentile compared to the 50th percentile of the knowledge capital stock of medium-income countries. It should be evident that the analysis presented here is really just a 'back-of-the-envelope' calculation, because we do not have access to the estimated coefficients for the two groups of countries separately.

Appendix 1: Our Sample Countries

The countries comprising our sample are: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Cyprus, Czechia, Denmark, Ecuador, Egypt, Finland, France, Germany, Greece, Guatemala, Hungary, Iceland, India, Ireland, Israel, Italy, Japan, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Netherlands, New Zealand, Norway, Pakistan, Panama, Philippines, Poland, Portugal, Romania, Russia, Singapore, Slovakia, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkiye, Ukraine, United Kingdom, United States, and Uruguay.

Appendix 2: The Model Variables

The model variables used in our empirical exercises are defined as below:

$Ln\ PAT\_PC$	Log of patent applications per capita
$Ln\ PAT\_PC\_GP1$	Log of patent publications per capita for technology group 1 industries
$Ln\ PAT\_PC\_GP2$	Log of patent publications per capita for technology group 2 industries
$Ln\ PAT\_PC\_GP3$	Log of patent publications per capita for technology group 3 industries
$Ln\ PAT\_PC\_GP4$	Log of patent publications per capita for technology group 4 industries
$Ln\ PAT\_PC\_GP5$	Log of patent publications per capita for technology group 5 industries
EDU	Number of years of education in the population aged 15 or more
$LKNOWK$	Log of Knowledge capital stock
GOV	Average of 'sub-index 1' (size of government) and 'sub-index 5' (regulation of credit markets, labour markets, and business) from the Economic Freedom dataset (Gwartney, Lawson, Murphy 2025)
$GOV2$	Worldwide Governance Index

$TECH\_LIC$	Technology Licensing – Royalty and license fee payments as a ratio of GDP
FDI_INF	Foreign Direct Investment inflow as a ratio of GDP
$TRADE$	Trade in goods and services as a ratio of GDP
$TRADE2$	Sub-index 4 of the Economic Freedom dataset (Gwartney, Lawson, Murphy 2025)
IPP	Intellectual property rights index
$IPP2$	Intellectual property rights index, with twice the weight on the implementation component

Appendix 3: The IP-intensive Technology Groups

The World Intellectual Property Organization provides a technology classification of patents based on the recommendations of Schmoch (2008). Using this classification, we create five technology groups which are intensive in intellectual property and for which patents are arguably significant instruments of appropriation (Cohen, Nelson and Walsh 2000). These technology groups are as follows:

(a) <u>Group 1: Electrical and Electronics Technology</u> – Audio-visual technology; Basic communication processes; Computer technology; Digital communication; Electrical machinery, apparatus, and energy; IT methods for management; Semiconductors; Telecommunications.

(b) <u>Group 2: Professional and Scientific Equipment</u> – Control; Measurement; Medical technology; Optics.

(c) <u>Group 3: Pharmaceuticals</u> – Pharmaceuticals.

(d) Group 4: Chemicals – Basic materials chemistry; Macromolecular chemistry, and polymers; Organic fine chemistry; Surface technology, and coating.

(e) Group 5: Machinery (Non-Electrical) – Engines, pumps, and turbines; Textile and paper machines; Other special machines.

After creating these five technology groups, we compute the total patent publications in each group, for each of the sample countries, for each sample year.

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Table 1: Descriptive Statistics for our Sample						
Variable	Units	Mean	Median	Standard Deviation	Minimum	Maximum
	(1)	(2)	(3)	(4)	(5)	(6)
PAT	Count	28960.63	1247.00	120825	2.00	1464605
PAT_GP1	Count	12501.77	271.00	46543.82	1.00	618178
PAT_GP2	Count	5820.79	266.00	20762.04	1.00	253110
PAT_GP3	Count	1487.79	129.50	4690.985	1.00	43628
PAT_GP4	Count	5159.47	322.50	18195.08	1.00	222526
PAT_GP5	Count	3086.17	181.50	10499.06	1.00	125223
PAT_PC	Count	0.000293	0.000079	0.000535	1.37e-07	0.003598
PAT_PC_GP1	Count	0.000173	0.000015	0.000329	4.18e-09	0.002144
PAT_PC_GP2	Count	0.000096	0.000017	0.000158	4.82e-09	0.000876
PAT_PC_GP3	Count	0.000038	0.000008	0.000079	4.74e-09	0.000596
PAT_PC_GP4	Count	0.000087	.000021	0.000160	5.02e-09	0.001321
PAT_PC_GP5	Count	0.000052	.000011	0.000083	3.00e-09	0.000689
$LPAT\_PC$	Count	-9.533948	-9.446460	1.948453	-15.801690	-5.627494
$LPAT\_PC\_GP1$	Count	-10.959630	-11.143880	2.730433	-19.293970	-6.145317
$LPAT\_PC\_GP2$	Count	-11.136379	-11.001720	2.522712	-19.151450	-7.040168
$LPAT\_PC\_GP3$	Count	-11.982040	-11.699120	2.343267	-19.167720	-7.425712
$LPAT\_PC\_GP4$	Count	-11.050830	-10.774760	2.320328	-19.110020	-6.629106
$LPAT\_PC\_GP5$	Count	-11.531710	-11.400840	2.350046	-19.623790	-7.279966
$LKNOWK$	PPP$ billion	4.863863	4.919178	2.883503	-2.356226	13.642860
$KNOWK$	PPP$ billion	10382.30	136.89	58131.89	0.094777	841429
EDU	Years	10.27813	10.75	1.972952	4.33	13.808
$EDU30$	Years	7.22255	7.493	2.451160	0.678	12.356
GOV	Index	6.719406	6.724557	0.717034	4.135875	8.457785
$TECH\_LIC$	Ratio	0.064399	.003626	1.256716	9.34e-06	42.01979
FDI_INF	Ratio	0.637269	.028024	12.191770	-4.447063	389.229400
$TRADE$	Ratio	0.896336	.695529	0.647739	0.1812568	4.373267
IPP	Index	4.610046	4.608272	0.692192	2.20568	5.858609

	Correlation Coefficients						
	$HUMK$	$LKNOWK$	GOV	$TECH\_LIC$	FDI_INF	$TRADE$	IPP
EDU	1.0000						
$LKNOWK$	0.1197	1.0000					
GOV	0.2746	-0.0851	1.0000				
$TECH\_LIC$	-0.0641	-0.0951	0.0003	1.0000			
FDI_INF	-0.0673	-0.1054	0.0025	0.9926	1.0000		
$TRADE$	0.2640	-0.3502	0.2420	-0.0187	-0.0225	1.0000	
IPP	0.6254	0.1744	0.2218	-0.0545	-0.0651	0.1054	1.0000

Notes: Number of observations = 1284;

PAT is patent applications; PAT_GPj is patent publications in technology group j (j = 1, …, 5); PAT_PC is patent applications per capita; PAT_PC_GPj is patent publications per capita in technology group j (j = 1, …, 5); $KNOWK$ is knowledge capital stock; $LPAT\_PC = Ln\ PAT\_PC$; $LPAT\_PC\_GPj = Ln\ PAT\_PC\_GPj$; $LKNOWK = Ln\ KNOWK$; EDU is average years of education in population aged 15+; $EDU30$ is EDU lagged 30 years; GOV is the governance index (average of 'size of government' and 'regulation' sub-indices of the Economic Freedom dataset (Gwartney et al. 2025); $TECH\_LIC$; is technology imports via licensing as a ratio of GDP; FDI_INF is foreign direct investment inflow as a ratio of GDP; $TRADE$ is exports plus imports of goods and services as a ratio of GDP; IPP is intellectual property protection index.

Table 2: Innovation and Educational Attainment – Baseline Regression						
	Dependent Variable: Aggregate and Disaggregated by Technology Group					
Variable	$LPAT\_PC$	$LPAT\_PC\_GP1$	$LPAT\_PC\_GP2$	$LPAT\_PC\_GP3$	$LPAT\_PC\_GP4$	$LPAT\_PC\_GP5$
	(1)	(2)	(3)	(4)	(5)	(6)
EDU	0.6728***	0.7405***	0.6539**	0.5552**	0.7116***	0.5172**
	(0.2264)	(0.2735)	(0.2855)	(0.2326)	(0.2182)	(0.2452)
$LKNOWK * EDU$	0.0227**	0.0284**	0.0365***	0.0392***	0.0356***	0.0381***
	(0.0112)	(0.0123)	(0.0131)	(0.0114)	(0.0103)	(0.0115)
GOV	0.2833*	0.3339*	0.3461*	0.2873**	0.1605	0.2302†
	(0.1485)	(0.1756)	(0.1738)	(0.1304)	(0.1562)	(0.1644)
$TECH\_LIC$	0.0289***	0.0391***	0.0956***	0.1105***	0.1022***	0.0539***
	(0.0043)	(0.0064)	(0.0071)	(0.0049)	(0.0047)	(0.0048)
FDI_INF	-0.0021	0.0144	0.0384***	0.0491***	0.0419***	0.0270***
	(0.0103)	(0.0182)	(0.0140)	(0.0120)	(0.0146)	(0.0089)
$TRADE$	0.1386	0.4280**	0.3461†	0.0010	0.0397	0.1452
	(0.1507)	(0.1896)	(0.2359)	(0.2530)	(0.2287)	(0.2038)
IPP	0.2702†	0.7038**	0.5488*	0.2113	0.3957†	0.4214†
	(0.1980)	(0.2868)	(0.2815)	(0.1916)	(0.2385)	(0.3065)
$\hat{\eta}$	-0.5737**	-0.5975*	-0.5891*	-0.4812*	-0.6214**	-0.5421*
	(0.2695)	(0.3140)	(0.3245)	(0.2715)	(0.2424)	(0.2845)
Intercept	-19.7990***	-25.1169***	-23.8265***	-21.9430***	-21.8537***	-21.3599***
	(2.9767)	(3.5294)	(3.5870)	(2.4482)	(2.6631)	(3.3436)
$N * T$	1284	1284	1284	1284	1284	1284
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value (H_0: $EDU = LKNOWK * EDU = 0$)	0.0085	0.0105	0.0083	0.0014	0.0007	0.0041
Semi-elasticity w.r.t EDU ($LKNOWK$ at median)	0.7844	0.8802	0.8335	0.7481	0.8868	0.7049
Semi-elasticity w.r.t EDU ($LKNOWK$ at 95th percentile)	0.8956	1.0193	0.5329	0.9401	1.0611	0.8917
R.M.S.E	0.3601	0.4912	1.0124	0.4957	0.4533	0.4888
Note: $\hat{\eta}$ is the residual term from the first stage regression of EDU on instruments I conditioned on confounders C; Clustered robust standard error in parentheses below the coefficient; ***, **, and * denote significance at the 1%, 5% and 10% levels, using a two-tail test; † denotes significance at the 10% level using a one-tail test R.M.S.E is root mean squared error						

Table 3: Innovation and Educational Attainment – Robustness Check: Alternative Generation Length++						
	Dependent Variable: Aggregate and Disaggregated by Technology Group					
Variable	$LPAT\_PC$	$LPAT\_PC\_GP1$	$LPAT\_PC\_GP2$	$LPAT\_PC\_GP3$	$LPAT\_PC\_GP4$	$LPAT\_PC\_GP5$
	(1)	(2)	(3)	(4)	(5)	(6)
EDU	0.5732**	0.6807***	0.6317**	0.5419**	0.6403***	0.4157*
	(0.2296)	(0.2516)	(0.2408)	(0.2139)	(0.2099)	(0.2382)
$LKNOWK * EDU$	0.0221*	0.0281**	0.0365***	0.0392***	0.0353***	0.0376***
	(0.0114)	(0.0124)	(0.0130)	(0.0113)	(0.0104)	(0.0117)
GOV	0.2824*	0.3334*	0.3460*	0.2873**	0.1599	0.2293†
	(0.1521)	(0.1777)	(0.1749)	(0.1315)	(0.1583)	(0.1676)
$TECH\_LIC$	0.0304***	0.0400***	0.0959***	0.1107***	0.1033***	0.0554***
	(0.0042)	(0.0060)	(0.0062)	(0.0051)	(0.0045)	(0.0047)
FDI_INF	0.0004	0.0159	0.0390***	0.0494***	0.0437***	0.0296***
	(0.0102)	(0.0177)	(0.0130)	(0.0117)	(0.0142)	(0.0085)
$TRADE$	0.1354	0.4263**	0.3458†	0.0010	0.0376	0.1419
	(0.1514)	(0.1881)	(0.2340)	(0.2542)	(0.2297)	(0.2022)
IPP	0.2623†	0.6989**	0.5468*	0.2100	0.3899†	0.4133†
	(0.1980)	(0.2870)	(0.2822)	(0.1928)	(0.2394)	(0.3065)
$\hat{\eta}$	-0.4578*	-0.5327*	-0.5718**	-0.4733*	-0.5424**	-0.4232
	(0.2702)	(0.2856)	(0.2699)	(0.2515)	(0.2296)	(0.2728)
Intercept	-18.8448***	-24.5461***	-23.6167***	-21.8185***	-21.1721***	-20.3868***
	(2.8137)	(3.2408)	(3.0926)	(2.2105)	(2.4346)	(3.1731)
$N * T$	1284	1284	1284	1284	1284	1284
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value ($H_0: EDU = LKNOWK * EDU = 0$)	0.0190	0.0084	0.0039	0.0008	0.0008	0.0058
Semi-elasticity w.r.t EDU ($LKNOWK$ at median)	0.6821	0.8191	0.8112	0.7348	0.8138	0.6006
Semi-elasticity w.r.t EDU ($LKNOWK$ at 95th percentile)	0.7906	0.9568	0.9898	0.9268	0.9864	0.7846
R.M.S.E	0.3638	0.4926	0.5048	0.4956	0.4553	0.4914
Note: ++ Generation length defined as 25 years for this exercise (compared to 30 years in the baseline results of Table 2); $\hat{\eta}$ is the residual term from the first stage regression of EDU on instruments I conditioned on confounders C; Clustered robust standard error in parentheses below the coefficient; ***, **, and * denote significance at the 1%, 5% and 10% levels, using a two-tail test; † denotes significance at the 10% level using a one-tail test; R.M.S.E is root mean squared error						

Table 4: Innovation and Educational Attainment – Robustness Check: Alternative Governance Index++						
	Dependent Variable: Aggregate and Disaggregated by Technology Group					
Variable	$LPAT\_PC$	$LPAT\_PC\_GP1$	$LPAT\_PC\_GP2$	$LPAT\_PC\_GP3$	$LPAT\_PC\_GP4$	$LPAT\_PC\_GP5$
	(1)	(2)	(3)	(4)	(5)	(6)
EDU	0.6754^{***}	0.7573^{***}	0.6848^{**}	0.5611^{**}	0.7145^{***}	0.5294^{**}
	(0.2230)	(0.2668)	(0.2792)	(0.2359)	(0.2065)	(0.2379)
$LKNOWK * EDU$	0.0208^{*}	0.0263^{**}	0.0344^{**}	0.0374^{***}	0.0344^{***}	0.0366^{***}
	(0.0113)	(0.0126)	(0.0134)	(0.0117)	(0.0102)	(0.0114)
$GOV2$	0.2302	0.5085^{**}	0.5057^{**}	0.2112	$0.2624^{\dagger}$	$0.3351^{\dagger}$
	(0.1824)	(0.2295)	(0.2338)	(0.1740)	(0.1681)	(0.2058)
$TECH\_LIC$	0.0311^{***}	0.0408^{***}	0.0960^{***}	0.1125^{***}	0.1033^{***}	0.0548^{***}
	(0.0048)	(0.0069)	(0.0076)	(0.0058)	(0.0053)	(0.0055)
FDI_INF	0.0030	0.0200	0.0436^{***}	0.0542^{***}	0.0447^{***}	0.0308^{***}
	(0.0094)	(0.0160)	(0.0116)	(0.0114)	(0.0134)	(0.0087)
$TRADE$	$0.2062^{\dagger}$	0.5163^{**}	0.4500^{*}	0.0715	0.0792	0.2086
	(0.1553)	(0.2012)	(0.2580)	(0.2915)	(0.2342)	(0.2030)
IPP	$0.1541^{\dagger}$	0.3676^{**}	0.2934^{**}	$0.1259^{\dagger}$	0.2046^{*}	$0.2225^{\dagger}$
	(0.1090)	(0.1437)	(0.1404)	(0.0948)	(0.1169)	(0.1508)
$\hat{\eta}$	-0.5710^{**}	-0.6106^{**}	-0.6183^{*}	-0.4821^{*}	-0.6228^{***}	-0.5522^{*}
	(0.2638)	(0.3054)	(0.3172)	(0.2734)	(0.2332)	(0.2796)
Intercept	-16.6875^{***}	-19.8079^{***}	-19.2897^{***}	-19.1108^{***}	-18.9815^{***}	-17.9985^{***}
	(2.1385)	(2.5157)	(2.6094)	(2.2204)	(1.9564)	(2.2516)
$N * T$	1284	1284	1284	1284	1284	1284
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value ($H_0: EDU = LKNOWK * EDU = 0$)	0.0072	0.0092	0.0089	0.0020	0.0006	0.0049
Semi-elasticity w.r.t EDU ($LKNOWK$ at median)	0.7777	0.8867	0.8540	0.7450	0.8837	0.7095
Semi-elasticity w.r.t EDU ($LKNOWK$ at 95th percentile)	0.8796	1.0154	1.0225	0.9279	1.0521	0.8889
R.M.S.E	0.3667	0.4971	0.5097	0.5006	0.4546	0.4913
Note: ++ Regressor $GOV2$ defined as the 'World Governance index' (Kaufmann and Kraay 2024) in this exercise (compared to GOV or governance index based on sub-indices 1 and 5 of the Economic Freedom dataset (Gwartney, Lawson, Murphy 2025) in the baseline results of Table 2); $\hat{\eta}$ is the residual term from the first stage regression of EDU on instruments I conditioned on confounders C; Clustered robust standard error in parentheses below the coefficient; ***, **, and * denote significance at the 1%, 5% and 10% levels, using a two-tail test; † denotes significance at the 10% level using a one-tail test R.M.S.E is root mean squared error						

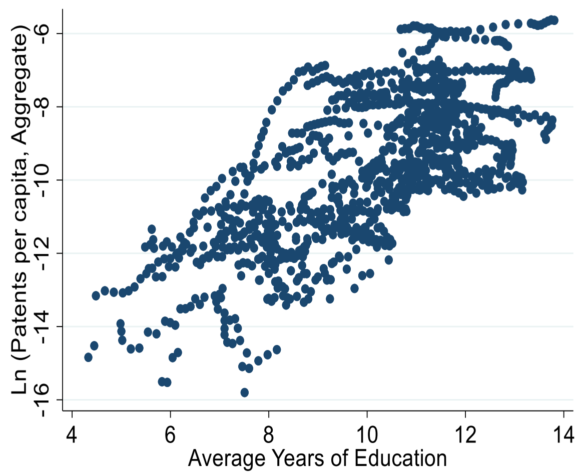
Table 5: Innovation and Educational Attainment – Robustness Check: Alternative Trade Measure++						
	Dependent Variable: Aggregate and Disaggregated by Technology Group					
Variable	$LPAT\_PC$	$LPAT\_PC\_GP1$	$LPAT\_PC\_GP2$	$LPAT\_PC\_GP3$	$LPAT\_PC\_GP4$	$LPAT\_PC\_GP5$
	(1)	(2)	(3)	(4)	(5)	(6)
EDU	0.6584***	0.7019**	0.6243**	0.5583**	0.7101***	0.5099**
	(0.2217)	(0.2652)	(0.2783)	(0.2278)	(0.2175)	(0.2434)
$LKNOWK * EDU$	0.0214*	0.0247*	0.0342**	0.0379***	0.0350***	0.0365***
	(0.0112)	(0.0124)	(0.0137)	(0.0112)	(0.0105)	(0.0118)
GOV	0.2918*	0.3190*	0.3871**	0.2087†	0.1620	0.2057
	(0.1636)	(0.1843)	(0.1855)	(0.1312)	(0.1566)	(0.1764)
$TECH\_LIC$	0.0289***	0.0399***	0.0949***	0.1124***	0.1022***	0.0545***
	(0.0041)	(0.0063)	(0.0073)	(0.0052)	(0.0052)	(0.0050)
FDI_INF	-0.0029	0.0124	0.0362**	0.0499***	0.0416***	0.0264***
	(0.0110)	(0.0198)	(0.0155)	(0.0122)	(0.0153)	(0.0094)
$TRADE2$	-0.0013	0.0639	-0.0332	0.1248†	0.0002	0.0522
	(0.0654)	(0.0819)	(0.0799)	(0.0896)	(0.0891)	(0.0824)
IPP	0.2679†	0.6793**	0.5486*	0.1840	0.3959†	0.4072†
	(0.2074)	(0.2940)	(0.2943)	(0.1951)	(0.2481)	(0.3130)
$\hat{\eta}$	-0.5491**	-0.5336*	-0.5404*	-0.4803*	-0.6153**	-0.5253*
	(0.2647)	(0.3064)	(0.3158)	(0.2680)	(0.2411)	(0.2843)
Intercept	-19.5569***	-24.6171***	-23.2270***	-22.2689***	-21.8014***	-21.3134***
	(2.9166)	(3.3941)	(3.4671)	(2.3482)	(2.5915)	(3.2842)
$N * T$	1284	1284	1284	1284	1284	1284
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value (H_0: $EDU = LKNOWK * EDU = 0$)	0.0091	0.0169	0.0132	0.0018	0.0010	0.0070
Semi-elasticity w.r.t EDU ($LKNOWK$ at median)	0.7638	0.8236	0.7924	0.7449	0.8821	0.6893
Semi-elasticity w.r.t EDU ($LKNOWK$ at 95th percentile	0.8687	0.9446	0.9596	0.9306	1.0533	0.8679
R.M.S.E	0.3615	0.4957	0.5083	0.4935	0.4535	0.4891
Note: ++ Regressor $TRADE2$ defined as sub-index 4 of the Economic Freedom dataset (Gwartney, Lawson, Murphy 2025) in this exercise (compared to $TRADE$ or exports and imports of goods and services as a ratio of GDP, used in the baseline results of Table 2); $\hat{\eta}$ is the residual term from the first stage regression of EDU on instruments I conditioned on confounders C; Clustered robust standard error in parentheses below the coefficient; ***, **, and * denote significance at the 1%, 5% and 10% levels, using a two-tail test; † denotes significance at the 10% level using a one-tail test R.M.S.E is root mean squared error						

Table 6: Innovation and Educational Attainment – Robustness Check: Larger weight on IPR Implementation++						
	Dependent Variable: Aggregate and Disaggregated by Technology Group					
Variable	$LPAT\_PC$	$LPAT\_PC\_GP1$	$LPAT\_PC\_GP2$	$LPAT\_PC\_GP3$	$LPAT\_PC\_GP4$	$LPAT\_PC\_GP5$
	(1)	(2)	(3)	(4)	(5)	(6)
EDU	0.6762***	0.7510***	0.6639**	0.5570**	0.7189***	0.5249**
	(0.2269)	(0.2754)	(0.2886)	(0.2339)	(0.2213)	(0.2476)
$LKNOWK * EDU$	0.0227**	0.0285**	0.0367***	0.0392***	0.0357***	0.0382***
	(0.0113)	(0.0125)	(0.0132)	(0.0114)	(0.0104)	(0.0115)
GOV	0.2793*	0.3244*	0.3398*	0.2837**	0.1560	0.2254†
	(0.1470)	(0.1756)	(0.1743)	(0.1312)	(0.1566)	(0.1648)
$TECH\_LIC$	0.0288***	0.0387***	0.0952***	0.1104***	0.1020***	0.0536***
	(0.0042)	(0.0064)	(0.0071)	(0.0049)	(0.0047)	(0.0048)
FDI_INF	-0.0021	0.0144	0.0382***	0.0492***	0.0417***	0.0268***
	(0.0103)	(0.0180)	(0.0138)	(0.0120)	(0.0145)	(0.0088)
$TRADE$	0.1424	0.4375**	0.3532†	0.0041	0.0447	0.1506
	(0.1493)	(0.1900)	(0.2348)	(0.2527)	(0.2276)	(0.2035)
$IPP2$	0.2670†	0.6899**	0.5316*	0.2116	0.3829†	0.4080†
	(0.1972)	(0.2860)	(0.2788)	(0.1906)	(0.2341)	(0.3031)
$\hat{\eta}$	-0.5772**	-0.6079*	-0.6002*	-0.4826*	-0.6299**	-0.5509*
	(0.2706)	(0.3157)	(0.3273)	(0.2735)	(0.2451)	(0.2864)
Intercept	-19.9808***	-25.5876***	-24.1891***	-22.0871***	-22.1146***	-21.6376***
	(3.0640)	(3.6775)	(3.7349)	(2.5170)	(2.7948)	(3.5199)
$N * T$	1284	1284	1284	1284	1284	1284
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value (H_0: $EDU = LKNOWK * EDU = 0$)	0.0086	0.0107	0.0085	0.0015	0.0008	0.0042
Semi-elasticity w.r.t EDU ($LKNOWK$ at median)	0.7878	0.8910	0.8442	0.7497	0.8946	0.7131
Semi-elasticity w.r.t EDU ($LKNOWK$ at 95th percentile)	0.8989	1.0304	1.0237	0.9415	1.0694	0.9004
R.M.S.E	0.3601	0.4915	0.5053	0.4957	0.4535	0.4891
Note: ++ Regressor $IPP2$ used in this exercise allows for twice the weight on the implementation component (compared to IPP used in the baseline results of Table 2); $\hat{\eta}$ is the residual term from the first stage regression of EDU on instruments I conditioned on confounders C; Clustered robust standard error in parentheses below the coefficient; ***, **, and * denote significance at the 1%, 5% and 10% levels, using a two-tail test; † denotes significance at the 10% level using a one-tail test R.M.S.E is root mean squared error						

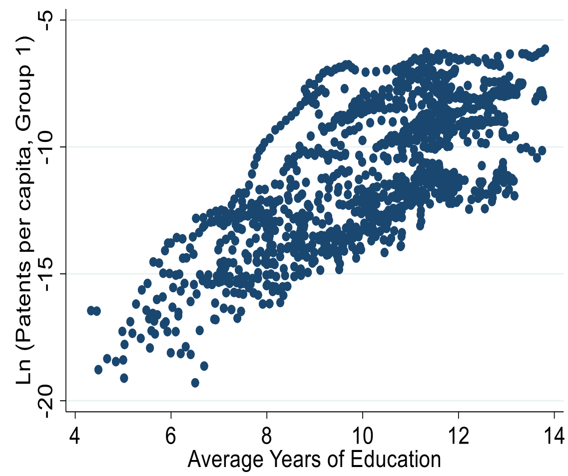
Table 7: Innovation and Educational Attainment – Robustness Check: Alternative specification with additional regressor++						
	Dependent Variable: Aggregate and Disaggregated by Technology Group					
Variable	$LPAT\_PC$	$LPAT\_PC\_GP1$	$LPAT\_PC\_GP2$	$LPAT\_PC\_GP3$	$LPAT\_PC\_GP4$	$LPAT\_PC\_GP5$
	(1)	(2)	(3)	(4)	(5)	(6)
EDU	0.6935***	0.7856***	0.6809**	0.5772**	0.7259***	0.5344**
	(0.2297)	(0.2763)	(0.2892)	(0.2567)	(0.2298)	(0.2548)
$LKNOWK * EDU$	0.0064	-0.0041	0.0207	0.0202	0.0292**	0.0293*
	(0.0137)	(0.0156)	(0.0176)	(0.0164)	(0.0121)	(0.0168)
$LKNOWK$	0.2079	0.4151*	0.2035	0.2423	0.0834	0.1139
	(0.2224)	(0.2164)	(0.2176)	(0.2248)	(0.1860)	(0.2398)
GOV	0.3091**	0.3838**	0.3689**	0.3184**	0.1679	0.2417†
	(0.1522)	(0.1827)	(0.1782)	(0.1306)	(0.1552)	(0.1648)
$TECH\_LIC$	0.0327***	0.0466***	0.0991***	0.1150***	0.1035***	0.0557***
	(0.0058)	(0.0067)	(0.0078)	(0.0063)	(0.0056)	(0.0062)
FDI_INF	-0.0020	0.0182	0.0401***	0.0514***	0.0425***	0.0279***
	(0.0105)	(0.0188)	(0.0142)	(0.0120)	(0.0145)	(0.0091)
$TRADE$	0.1121	0.3771**	0.3236†	-0.0311	0.0326	0.1341
	(0.1420)	(0.1726)	(0.2328)	(0.2517)	(0.2285)	(0.2013)
IPP	0.1988†	0.5538*	0.4649†	0.1321	0.3555†	0.3707
	(0.2237)	(0.3243)	(0.3036)	(0.2026)	(0.2291)	(0.3195)
$\hat{\eta}$	-0.5216**	-0.4968	-0.5458*	-0.4178	-0.6076***	-0.5204*
	(0.2488)	(0.2978)	(0.3187)	(0.2629)	(0.2249)	0.2727)
Intercept	-20.1919***	-26.0091***	-24.3957***	-22.3332***	-22.1993***	-21.7532***
	(3.1324)	(3.8461)	(3.8002)	(2.8238)	(2.9170))	(3.6252)
$N * T$	1284	1284	1284	1284	1284	1284
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value ($H_0: EDU = LKNOWK * EDU = 0$)	0.0079	0.0219	0.0424	0.0091	0.0002	0.0203
Semi-elasticity w.r.t EDU ($LKNOWK$ at 50th percentile	0.7248	0.7654	0.7826	0.6763	0.8693	0.6786
Semi-elasticity w.r.t EDU ($LKNOWK$ at 95th percentile	0.7560	0.7452	0.8839	0.7750	1.0121	0.8221
R.M.S.E	0.3567	0.4813	0.5031	0.4924	0.4533	0.4885
Note: ++ Variable $LKNOWK$ is included as an additional control; $\hat{\eta}$ is the residual term from the first stage regression of EDU on instruments I conditioned on confounders C; Clustered robust standard error in parentheses below the coefficient; ***, **, and * denote significance at the 1%, 5% and 10% levels, using a two-tail test; † denotes significance at the 10% level using a one-tail test R.M.S.E is root mean squared error						

Figure 1: Scatterplots for the Innovation-Education relationship

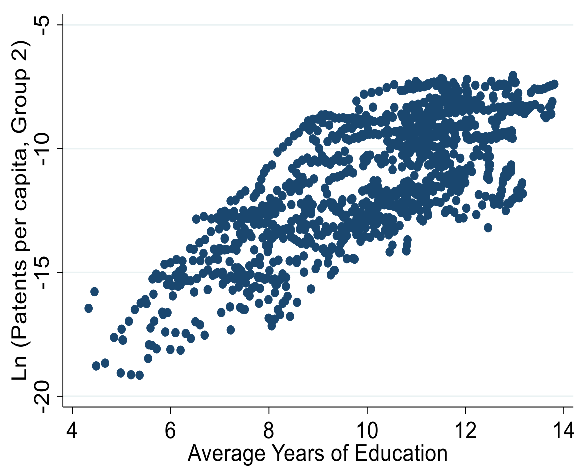
(a) Scatterplot for Aggregate Innovation



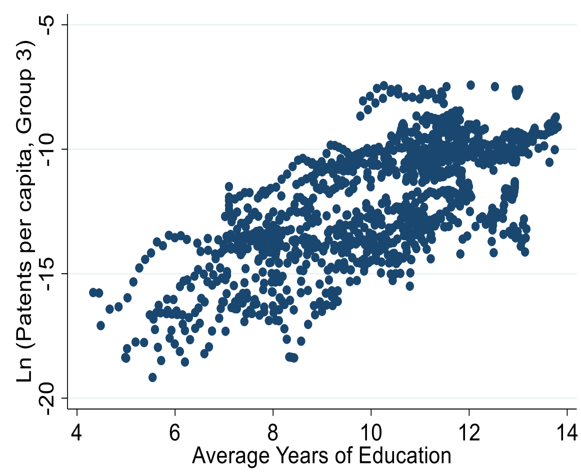
(b) Scatterplot for Group 1 industries



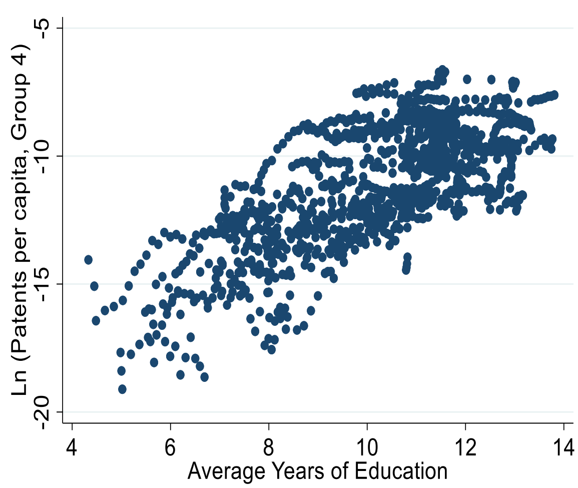
(c) Scatterplot for Group 2 industries



(d) Scatterplot for Group 3 industries



(e) Scatterplot for Group 4 industries



(f) Scatterplot for Group 5 industries

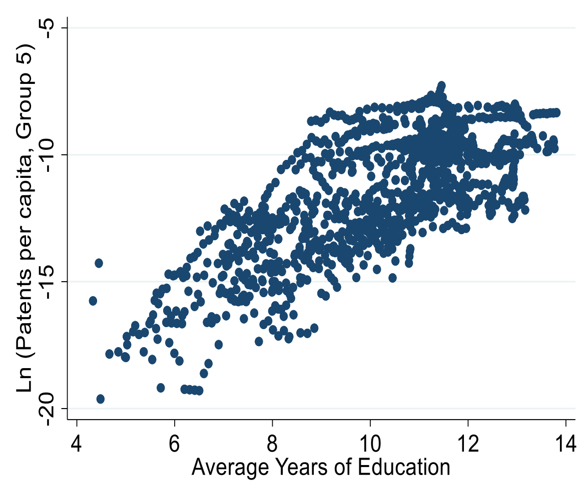
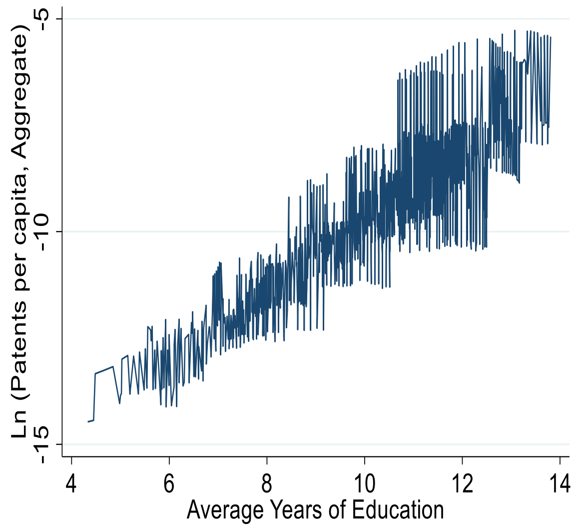
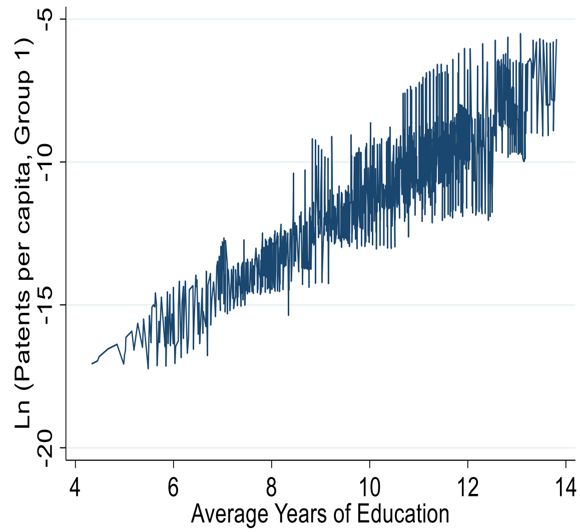


Figure 2: Plots of Estimated Innovation on Education

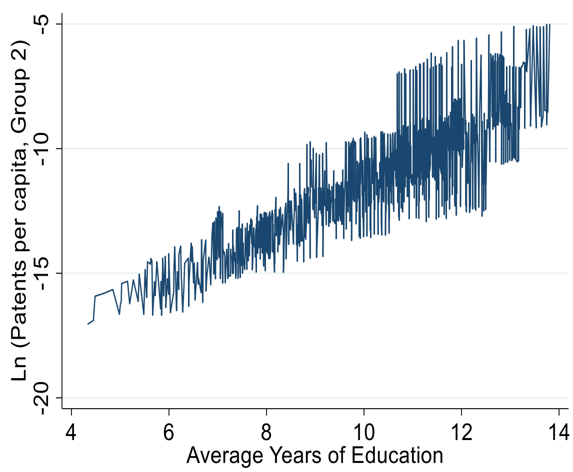
(a) Plot for Aggregate Innovation



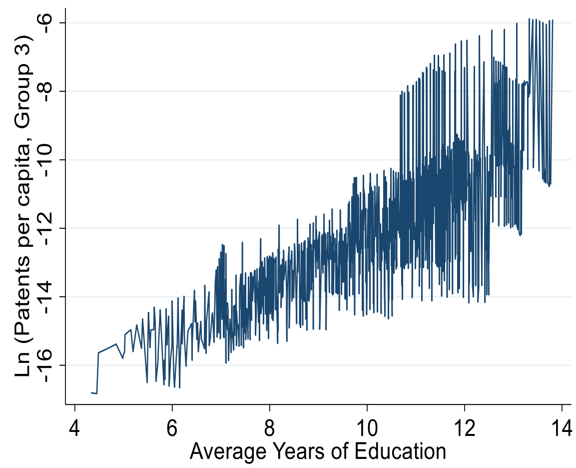
(b) Plot for Group 1 industries



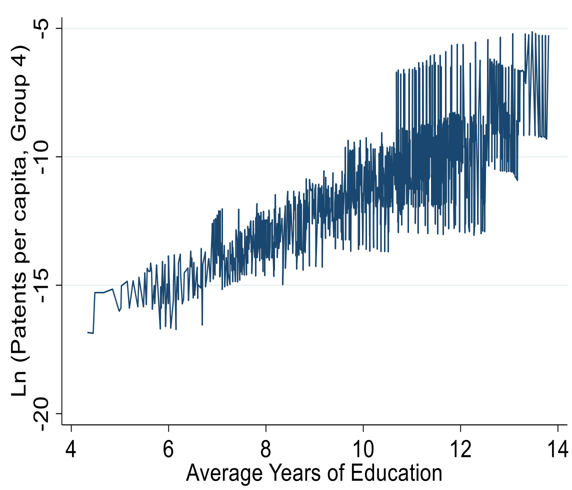
(c) Plot for Group 2 industries



(d) Plot for Group 3 industries



(e) Plot for Group 4 industries



(f) Plot for Group 5 industries