Human Capital, Its Constituents, and Entrepreneurial Innovation: A Multi-Level Modelling of Global Entrepreneurship Monitor Data

Vijay Vyas and Renuka Vyas

"Innovation has nothing to do with how many R&D dollars you have... It's not about money. It's about the people you have."


In this study, we use multi-level modelling to analyze data of over 200,000 businesses in 96 countries to explain the failure of previous research to extend human capital theory to innovation. We trace this failure to, previously overlooked, conflicting influences of education and experience. The two key constituents of human capital are often used in research as innovation antecedents and present a conceptual and empirical case against the use of work experience as a constituent of human capital. Our hierarchical exploration of innovation antecedents shows that, at the individual level, being young and recently educated are significant predictors of innovation whereas, at the societal level, national wealth dampens the negative effect of age on innovation and accentuates the positive effect of education on it.

Introduction

Recently, the role of human capital in entrepreneurship has attracted substantial scholarly interest (Dimov, 2017; Dutta & Sobel, 2018; Marvel et al., 2016; Unger et al., 2011). Within the resulting literature, studies on the link between human capital and innovation have yielded counterintuitive and conflicting results (Wincent et al., 2010). Subramaniam and Youndt (2005), for instance, report that human capital is adversely related to radical innovation capability, Marvel and Lumpkin (2007) find that market knowledge is negatively influences radical innovation, and Delgado-Verde and co-authors (2016) do not find support for their proposed inverted U-shaped positive effect of human capital on radical innovation. At the same time, many studies examining this relationship report a positive link (e.g., Colombo et al., 2017; Crespo & Crespo, 2016; Kianto et al., 2017; Miguélez et al., 2011; Rupietta & Backes-Gellner, 2017).

Teixeira and Fortuna (2010) argue that, “human capital is generally poorly proxied, and measurement problems are particularly acute when it comes to this variable”. We advance this argument further and clarify the cause of the conflicting findings described above. We find that education, experience, or both are often used as the building blocks of human capital and the empirical research has frequently measured the outcome of the impact of education or experience or education plus experience on innovation. However, as we show below, experience and education leverage innovation in opposite directions, therefore when the relationship between human capital and innovation is empirically tested, the outcomes turn out to be divergent. More specifically, as Table 1 shows, when human capital is articulated purely in terms of educational attainment or where experience is excluded from the calculus of its measurement, the effect of human capital on innovation is invariably positive. In contrast, when human capital is measured purely in experience terms or when experience is a part of its calculus, an analysis of its influence on innovation often yields a negative or non-significant relationship.

Work experience as human capital: The conceptual incongruity

Ostrom and Ahn (2009), observe that “All forms of capital involve the creation of assets by allocating resources that could be used up in immediate consumption to create assets that generate a potential
Human Capital, Its Constituents, and Entrepreneurial Innovation
Vijay Vyas and Renuka Vyas

flow of benefits over a future time horizon." The creation of human capital, too, thus involves diverting resources from current consumption and investing them to generate a potential flow of future benefits. This happens when people invest in education, training, or health or when they allot time and money to migrate to places where they hope to have better incomes and lives. All of these actions, therefore, give rise to human capital. However, when people take up employment and begin to accumulate work experience, they do it primarily to earn immediate benefits. This is a key difference between education and work experience, two potential enhancers of human productivity. People seek education principally for future economic benefits whereas they seek employment primarily for current benefits. Further, investment entails diversion of

Table 1. Performance influence of human capital

<table>
<thead>
<tr>
<th>Source</th>
<th>Human Capital Constituents</th>
<th>Performance Measures</th>
<th>Selected Relevant Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subramaniam &amp; Youndt (2005)</td>
<td>Knowledge, skills, and ability (KSA)</td>
<td>Radical innovation capability</td>
<td>Negative effect</td>
</tr>
<tr>
<td>Rodriguez-Pose &amp; Crescenzi (2008)</td>
<td>Education</td>
<td>Regional innovation</td>
<td>Positive effect</td>
</tr>
<tr>
<td>Teixeira &amp; Fortuna (2010)</td>
<td>Education</td>
<td>Total factor productivity</td>
<td>Substantial positive effect</td>
</tr>
<tr>
<td>Wincent et al. (2010)</td>
<td>Board’s education and diversity</td>
<td>Innovative performance of network participants</td>
<td>Positive effect</td>
</tr>
<tr>
<td>Al-Laham et al. (2011)</td>
<td>Education and tenure</td>
<td>Patents renewal</td>
<td>Education has positive and tenure has negative effect</td>
</tr>
<tr>
<td>Miguelez et al. (2011)</td>
<td>Education</td>
<td>Number of patents</td>
<td>Positive effect</td>
</tr>
<tr>
<td>Robson et al. (2012)</td>
<td>Education and experience</td>
<td>Engagement in innovation activities</td>
<td>Experience strong positive effect, education weak effect</td>
</tr>
<tr>
<td>Castellacci &amp; Natera (2013)</td>
<td>Education</td>
<td>Innovation dynamics (ID): per capita growth (PCG) on ID and of tertiary education on PCG</td>
<td>Positive effect of secondary education on ID and of tertiary education on PCG</td>
</tr>
<tr>
<td>Belso-Martinez et al. (2013)</td>
<td>Education, research experience</td>
<td>Performance of new innovative firm</td>
<td>No effect</td>
</tr>
<tr>
<td>Felsenstein (2015)</td>
<td>Education</td>
<td>Regional innovation</td>
<td>Large positive effect</td>
</tr>
<tr>
<td>McGuirk et al. (2015)</td>
<td>Education, training, and others</td>
<td>Product, process, and service innovation</td>
<td>Positive effect of training</td>
</tr>
<tr>
<td>Delgado-Verde et al. (2016)</td>
<td>KSA</td>
<td>Radical innovation</td>
<td>Inverted U-shaped positive effect not supported</td>
</tr>
<tr>
<td>Crespo &amp; Crespo (2016)</td>
<td>Education</td>
<td>Knowledge, technology, and creative outputs</td>
<td>Positive effect</td>
</tr>
<tr>
<td>Rupietta &amp; Backes-Gellner (2017)</td>
<td>Education</td>
<td>Incremental innovation</td>
<td>Human capital a key component of innovation affecting configuration</td>
</tr>
<tr>
<td>Colombo et al. (2017)</td>
<td>Education</td>
<td>R&amp;D investments</td>
<td>Positive effect</td>
</tr>
</tbody>
</table>
resources from current consumption for future potential benefits. This happens with education but not with employment. Employment, therefore, is not investment and the work experience that it provides is not human capital. Finally, as Becker (1964) suggests, “forgone earnings are an important, although neglected cost of much investment in human capital”. Forgone earnings are obvious in education. However, usually there are no forgone earnings in the process of gaining work experience. We argue that, unless we are able to trace the origin of a productive human advantage to some form of investment of resources diverted from current consumption or to some forgone earnings, what we have is not human capital. It is therefore conceptually wrong to consider work experience a constituent of human capital.

In this article, we first provide a review of literature on human capital underscoring the contribution of key pioneers of this concept. We then present our primary as well as moderating hypotheses and the conceptual and empirical logic underpinning them. Data and measures used in this work are then elaborated and variables are specified. This is followed by our rationale for using multi-level modelling as well as the details of the data analysis process. Finally, we discuss our results, highlight our contribution and spell out the limitations of this work, its future research directions, as well as its policy implications.

**Literature Review: Human Capital**

Though traces of human capital doctrine could be seen in Adam Smith’s writing as early as 1776 (Smith, 1952), it was not until the 1960s that human capital emerged as an influential contribution to enhancements in human productivity in the economic growth process. Becker’s (1964) definition of human capital, as “the knowledge, information, ideas, skills, and health of individuals” (Becker, 2002) is, essentially, not much different from its modern perception as “the characteristics possessed by... individual(s) that can yield positive outcomes for (them)” (Wright & McMahan, 2011).

Schultz and Becker contributed most to the early articulation of human capital doctrine and in estimating its contribution in the calculus of economic growth. Its basic premise was that individuals accumulate productive human capital over time by way of knowledge, skills, and expertise and investments in human capital, particularly in education, account for a significant part of economic growth (Becker, 1962, 1964; Schultz, 1960, 1961). Pioneering work on the role of human capital in economic growth was duly rewarded. Starting with Schultz and Becker, five Nobel prizes in economic sciences were awarded to scholars for their contributions in this field, with the other three going to Milton Friedman, Simon Kuznets, and Robert Solow (Sweetland, 1996).

Despite wide acceptance of the value of human capital construct in explaining economic growth, the analyst who pioneered the concept diverged on what were its precise building blocks, something which remains unchanged until now, as we have shown above. Schultz’s (1961) configuration included health services, on-the-job training, education, and migration, whereas Becker (1964) included education, on the job training, information, and health. Contrary to the impression in some of the recent literature (e.g., Cao & Im, 2018; Davidsson & Honig, 2003; Marvel & Lumpkin, 2007), Becker (1962, 1964) did not include work experience as a component of human capital in his analysis (and, as stated above, neither did Schultz [1960, 1961]). Among the pioneers, Mincer (1974) was conspicuous for his inclusion of work experience as a component of human capital and, in all likelihood, was responsible for a tradition of its inclusion in it that continues until today.

We believe that, to unpick the contribution of human capital’s various candidate elements in the innovation process, it is imperative that we decompose it into its key postulated constituents to better understand their individual roles in entrepreneurial innovation. Using age as a proxy for experience, we have attempted it here.

**Hypothesis Development**

**Education and innovation**

At the start of 20th century, formal education gradually began to be seen as a vital influence on innovation (Nelson & Rosenberg, 1993), and this continues to be the case. Holbrook and Clayman (2003) report that tertiary education develops the innovative skills of recipients. Leiponen (2005) shows that high educational levels complement product and process innovation. Vila and co-authors (2012) report that learning and teaching modes used in higher education develop innovation competencies. Investments in education explain a significant part of rise in total factor productivity in Portugal (Teixeira & Fortuna, 2010) as well as across the European Union (Bonin, 2017). Crespo and Crespo (2016) show that a high “level and standard of education” is linked with high innovation performance. Colombo and co-authors (2017) report that the share of employees with at least a university degree in the workforce is a significant predictor of R&D-to-Sales
Human Capital, Its Constituents, and Entrepreneurial Innovation

Vijay Vyas and Renuka Vyas

ratio. Given the evidence on the nexus between education and innovation in such a range of milieus (Arvanitis & Stucki, 2012), we argue that the premise that an entrepreneurs’ education would positively influence innovation in their enterprises follows logically and naturally.

We thus hypothesize that:

**Hypothesis 1:** Entrepreneur education positively influences innovation in their enterprises.

**Age and innovation**
The balance of evidence on the relationship between age and innovation decisively points to a negative connection. Pfeifer and Wagner (2012) record a strong adverse impact of average age on several innovation-linked indicators. Schubert and Andersson (2015) find the age of an individual to be negatively related to their innovation performance, and Amtz and Gregory (2014) show that 17% of the gap in regional innovation performance in Germany is explained by demographic aging. In a related context, Jones (2010) reports scientists’ peak creative productivity in middle age, which is followed by declining performance. We found only one study (Ng & Feldman, 2013a) that positively links age with innovation-related behaviour. However, the same authors did not find such a relationship an earlier study (Ng & Feldman, 2008) or in their meta-analysis (Ng & Feldman, 2013b). These findings indicate that the evidence for a positive relationship is limited and sketchy. Furthermore, it is shown that the innovative advantage of the young lies in their higher risk tolerance (Lèvesque & Minniti, 2006) and in the contemporariness of their technological skills (Ouimet & Zarutskie, 2011).

We thus hypothesize that:

**Hypothesis 2:** Entrepreneur age is negatively linked with innovation in their enterprises.

**National income and innovation**
Despite the widely recognized causal nexus of innovation with competitiveness, growth, and economic prosperity, the potential inverse causation between current levels of national income and future innovation has not been theoretically discussed or empirically tested. We argue that the nature and direction of causality here can be deduced from the findings of works on the relationship of current levels of per capita income with future prospects of growth. Barro’s (1991) finding that “higher per capita GDP is substantially negatively related to subsequent per capita (income) growth” and his more recent estimate of “conditional convergence rate around 2% per year” (Barro, 2015) indicate that highly innovative nations are likely to have slower future increases in their innovativeness. This result is also inferred from Kortum’s (1997) search model, which shows that technological advances push a nation closer to the technological frontier and decrease the technological gap, ceteris paribus, diminishing its future innovation potential. Conversely, from the convergence literature, Gerschenkron’s (1952) conception of “advantage of backwardness” implies that further a country stands behind the technology frontier, larger it has the scope for innovation.

We thus hypothesize that:

**Hypothesis 3:** Per capita income of a country is negatively related to innovation in its enterprises.

Next, we consider moderating hypotheses.

**Effect of age on the relationship between education and innovation**
We argue that the ability of entrepreneurs to utilize their formal education for innovation will diminish with age on the premise that the general decline in the value of knowledge with time (Frosch & Tivig, 2007) applies to its value for innovation as well. Innovation involves the creation of new products, processes, and forms of organizations that perform better than the existing ones. We argue that the entrepreneurs’ ability to innovate depends on the contemporariness of their knowledge. Up-to-date knowledge related to products, processes, and organizations is a prerequisite to conceptualize, create, and use their future and better versions. The earlier the acquisition of knowledge is, the more primeval the products, processes, and organizations are that it relates to. Frosch and Tivig (2007) find that, “engineering knowledge and, to a smaller extent, formal academic knowledge lose their innovation-enhancing effect when the labor force grows older”. Further, as Simonton’s (1988) work shows, the “ideations’ ability — the knack to visualise a new realm of possibility by recombining knowledge —diminishes with age as the fluid intelligence falls (Kanfer & Ackerman, 2004), leading to a reduced ability of an entrepreneur to take advantage of their knowledge for innovation.

We thus hypothesize that:

**Hypothesis 2a:** Entrepreneur age negatively moderates the effect of education on innovation in their enterprises.
Human Capital, Its Constituents, and Entrepreneurial Innovation

Vijay Vyas and Renuka Vyas

Effect of national wealth on relationships of age and education with innovation

Entrepreneurs’ efforts to utilize their education and age-related competencies for innovation could be supported or hindered by the environments within which they operate. The national system of innovation perspective posits that, in relation to the ability of an individual to innovate, the role of “the national education system, industrial relations, technical and scientific institutions, government policies, cultural traditions and many other national institutions is fundamental” (Freeman, 1995). Innovation-enabling overarching national characteristics include the quality and extensiveness of higher education (Lundvall, 2008), the calibre of public and private research institutions (Albuquerque et al., 2015), and the value national governments place on innovation as well as their ability and preparedness to support it (Watkins et al., 2015). The potential of these innovation-enabling influences is closely connected to the levels of national wealth. Countries with high per capita income have, in general, better universities and research organizations as well as more transparent, efficient, and effective governments. As a result, other things being equal, entrepreneurs engaging in innovation in affluent countries find themselves operating in more enabling environments. They are thus able to use their education for innovation more successfully than entrepreneurs are in poorer countries. The superiority of innovation-enabling environments in wealthier countries also weakens the negative effect of age on an entrepreneurs’ ability to innovate.

We thus hypothesize that:

Hypotheses 3a: Per capita national income positively moderates the effect of education on innovation.

Hypotheses 3b: Per capita national income negatively moderates the effect of age on innovation.

Data and Measurements

Data

The gross national income per capita (GNI) data for this work is taken from the Human Development Index (UNDP, 2014). The rest of the data comes from Global Entrepreneurship Monitor’s (GEM) Adult Population Surveys (APS) from 2005 to 2011 in 96 countries.

Figure 1. Conceptual model
Human Capital, Its Constituents, and Entrepreneurial Innovation

Vijay Vyas and Renuka Vyas

(Reynolds et al., 2005). GEM data is well recognized for its quality, and its use has made significant contribution to entrepreneurship research over many years (Levie et al., 2014). For the APS, a minimum of 2,000 randomly chosen adults are interviewed in each participating country in a survey commissioned by GEM’s respective country teams. All consequent data is weighted by relevant demographic variables to harmonize it and make it as representative as possible of the respective countries’ adult populations (Reynolds et al., 2005 provide a detailed explanation of the GEM method). The APS data constitutes a fairly representative sample of adults in surveyed countries. From this sample, 210,554 owner-managers of existing businesses are sub-sampled for analysis here. The findings are therefore generalizable to the universe of all firms in these countries (Schott & Jensen, 2016).

The GEM model generates multi-level data (Levie & Autio, 2008), which can be used to draw meaningful inferences only through multi-level modelling (Carson & Beeson, 2013), as we have attempted here.

Dependent variable
Innovation is measured from the data generated by the answers to three APS questions given below:

1. “Will all, some, or none of your potential customers consider this product or service new and unfamiliar?” The useable answers and related original data values (in parenthesis), vary between, all (1), some (2), and none (3).

2. “Right now, are there many, few, or no other businesses offering the same products or services to your potential customers?” The useable answers and related original data values (in parenthesis), vary between, many business competitors (1), few business competitors (2), and no business competitors (3).

3. “Have the technologies or procedures required for this product or service been available for less than a year, or between one to five years?” The useable answers and related original data values (in parenthesis), vary between less than a year (1), between one to five years (2), and longer than five years (3).

For questions 1 and 3 above, higher data values imply lower innovation. The data reversal is therefore applied to generate the data sets with higher values implying higher innovation. After confirming statistically significant positive correlations among the data sets, with two of them so modified, a new variable “Innovation” is created by adding the mean of data values for three innovation-related questions. This means that the innovation so measured covers product as well as process innovation but excludes organizational innovation.

Independent variables
Entrepreneur age is self-reported chronological age. It varies between 18 years to 64 years in APS data.

Entrepreneur education is self-reported years of formal education. It varies between 0 to 19 years in our data.

GNI is Gross national income per capita (in 2011) taken from Human Development Index (UNDP, 2014). It is expressed in thousands of Purchasing Power Parity dollars and varies between 0.715 for Malawi and 72.371

**Table 2.** Correlations and descriptive statistics

<table>
<thead>
<tr>
<th>Correlations</th>
<th>Opport</th>
<th>Noefail</th>
<th>Gender</th>
<th>Age</th>
<th>Education</th>
<th>GNI</th>
<th>INNO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opport</td>
<td>.138</td>
<td>.111</td>
<td>.002</td>
<td>-.128</td>
<td>-.040</td>
<td>.081</td>
<td>-</td>
</tr>
<tr>
<td>Suskill</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Noefail</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GNI</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INNO</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Descriptive Statistics**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opport</td>
<td>.57</td>
<td>.50</td>
<td>165106</td>
</tr>
<tr>
<td>Noefail</td>
<td>.74</td>
<td>.44</td>
<td>204027</td>
</tr>
<tr>
<td>Gender</td>
<td>.61</td>
<td>.49</td>
<td>210514</td>
</tr>
<tr>
<td>Age</td>
<td>40.12</td>
<td>11.65</td>
<td>210554</td>
</tr>
<tr>
<td>Education</td>
<td>.58</td>
<td>4.63</td>
<td>205808</td>
</tr>
<tr>
<td>GNI</td>
<td>21.77</td>
<td>14.6</td>
<td>210481</td>
</tr>
<tr>
<td>INNO</td>
<td>1.48</td>
<td>.47</td>
<td>210554</td>
</tr>
</tbody>
</table>

*** Correlation is significant at the 0.01 level (2-tailed)
Human Capital, Its Constituents, and Entrepreneurial Innovation

Vijay Vyas and Renuka Vyas

for Singapore.

Control variables
We have used four control variables for our analysis. A prerequisite for innovation is that the innovator is ‘not constrained by a fear of failure’ (Amabile & Kharie, 2008). We therefore expect fear of failure to be negatively related to innovation. By reversing the Fearfail variable in GEM data, we have recorded it as Nofearfail with 0 if answer is “yes” and 1 if it is “no” to the APS question “Fear of failure would prevent you from starting a business.” As ability to spot opportunities is at the core of innovation (Gailly, 2018), we have included, as a control variable, Opprof from the APS, which is a measure of entrepreneur’s ability to “perceive good business opportunities”. The APS variable Suskill, which measures an entrepreneur’s knowledge and skills in starting a business, is our third control variable. We have chosen it based on the argument that knowledge and skills needed to start a new business would also be useful in introducing a new product, new service, or a new way of doing business. Though Gender as an innovation influence continues to be under-researched, particularly within entrepreneurship literature, it is now increasingly recognized as an important influence on innovation (Alsos, et al. 2012); we have therefore included it as our fourth control variable.

Random effects variable
In our multi-level model (MLM), we have used Country, in GEM data, as the random effects variable.

Correlations matrix and descriptive statistics
The correlations, means, and standard deviations of the variables involved in this analysis are given in Table 2. Correlations of all control variables with innovation are statistically significant. All three hypothesized independent variables are also significantly correlated with innovation at P < 0.01, and the directions of correlations are as postulated. However, no set of independent variables are highly correlated (Pearson correlation coefficient > 0.5). This finding rules out multicollinearity. These results also show that entrepreneurs from wealthier countries are older and more educated. However, they are less innovative, indicating a more powerful combined negative influence of age and national wealth on innovation than that of education. They also reveal that the younger entrepreneurs are more educated and are more innovative. One noteworthy finding from this analysis is that, globally, woman entrepreneurs are marginally more innovative than men, and this difference is statistically significant.

Data Analysis and Results
We deploy MLM to examine the influence of entrepreneur age, education, and per capita national income of their countries on innovation with random effects of their national location through the variable Country.

Random effects model
After generating the Null model with baseline values, we first test if the variable Country has valid random effects within MLM estimation procedure. The following equation for this model postulates that observed Innovation (I) is explained by the general intercept (γ0), the random effects of Country (μc) and by a random error (or unexplained variance) (ε):

\[ I = γ0 + μc + ε \]

The results of this model are summarized in Table 3, Model 2, which show that random effects of country (μc) are highly significant are highly significant (p < 0.001), indicating, as postulated, that observed innovation varies across countries. The variable Country, therefore, can be justifiably included in the predictor model as random effects.

MLM with controls
We now use MLM to test if opportunity perception, start-up skills, no fear of failure, and gender are valid influences on innovation to be used as control variables. Level 1 (individual level) variables such as these control variables as well as the predictors with a raw metric with no meaningful zero point must be centred to have correct interpretation of results in multi-level modelling (Enders & Tofghi, 2007). As our focus is on an individual-level variable, entrepreneurial innovation, we need to deploy grand mean centring for this purpose (Carson & Beeson, 2013). We use this to centre control variables as well as to centre all predictors subsequently.

The MLM equation at this stage postulates that, in addition to the general intercept (γ0), the random effect of country (μc) and the random error (ε), opportunity perception (γopport), start-up skills (γsuskil), no fear of failure (γnff) and gender (γgender) explain the observed innovation further.

\[ I = γ0 + γopport + γsuskil + γnff + γgender + μc + ε \]

The results of this model, summarized in Table 3, reveal fixed effects of all control variable as well as random effects of variable Country to be highly significant (p < 0.001).
Table 3. Results

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Regression</td>
<td>Coefficients (Fixed Effects)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>1.480864</td>
<td>(.0010)**</td>
<td>1.493928</td>
<td>(.015893)**</td>
<td>1.506891</td>
</tr>
<tr>
<td>Opport</td>
<td>.058695</td>
<td>(.002298)**</td>
<td>.051999</td>
<td>(.002306)**</td>
<td>.051999</td>
</tr>
<tr>
<td>Susskill</td>
<td>.023829</td>
<td>(.003131)**</td>
<td>.017876</td>
<td>(.003159)**</td>
<td>.018082</td>
</tr>
<tr>
<td>NoFearful</td>
<td>.023855</td>
<td>(.002469)**</td>
<td>.021059</td>
<td>(.002494)**</td>
<td>.021182</td>
</tr>
<tr>
<td>Gender</td>
<td>-.019678</td>
<td>(.002215)**</td>
<td>-.018723</td>
<td>(.002223)**</td>
<td>-.018720</td>
</tr>
<tr>
<td>GNI</td>
<td>-.061051</td>
<td>(.000929)**</td>
<td>-.301105</td>
<td>(.000927)**</td>
<td>-.301105</td>
</tr>
<tr>
<td>Age</td>
<td>-.063110</td>
<td>(.000996)**</td>
<td>-.303146</td>
<td>(.000996)**</td>
<td>-.303146</td>
</tr>
<tr>
<td>Education</td>
<td>.000276</td>
<td>(.000266)**</td>
<td>.006440</td>
<td>(.000271)**</td>
<td>.006440</td>
</tr>
<tr>
<td>Age*Edu</td>
<td>-.300012</td>
<td>(.000021)**</td>
<td>-.300012</td>
<td>(.000021)**</td>
<td>-.300012</td>
</tr>
<tr>
<td>GNI*Age</td>
<td>-.300098</td>
<td>(.000067)**</td>
<td>-.300098</td>
<td>(.000067)**</td>
<td>-.300098</td>
</tr>
<tr>
<td>GNI*Edu</td>
<td>.000042</td>
<td>(.000019)**</td>
<td>.000042</td>
<td>(.000019)**</td>
<td>.000042</td>
</tr>
<tr>
<td>Variance Components</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Country</td>
<td>.219925</td>
<td>(.000067)**</td>
<td>.201311</td>
<td>(.000062)**</td>
<td>.200243</td>
</tr>
<tr>
<td>Residual</td>
<td>.022057</td>
<td>(.000067)**</td>
<td>.021008</td>
<td>(.000067)**</td>
<td>.020242</td>
</tr>
<tr>
<td>Model Summary</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance stat (-2LL)</td>
<td>278648.812</td>
<td></td>
<td>260512.894</td>
<td></td>
<td>223123.933</td>
</tr>
<tr>
<td># of estimated</td>
<td>2</td>
<td></td>
<td>3</td>
<td></td>
<td>7</td>
</tr>
<tr>
<td>parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N (Individuals)</td>
<td>210354</td>
<td></td>
<td>210354</td>
<td></td>
<td>179447</td>
</tr>
<tr>
<td>N (Countries)</td>
<td>96</td>
<td></td>
<td>96</td>
<td></td>
<td>96</td>
</tr>
</tbody>
</table>
Human Capital, Its Constituents, and Entrepreneurial Innovation

Vijay Vyas and Renuka Vyas

MLM with predictors
Now we enter our centred predictors in MLM as per the equation below:

\[ I = \gamma_0 + \gamma_{opportunity} + \gamma_{suskil} + \gamma_{nff} + \gamma_{gender} + \gamma_{age} + \gamma_{edu} + \gamma_{NI} + \mu_{C + \varepsilon} \]

This brings into play age (education), and per capita national income as innovation influencing factors. The results of this model, summarized in Table 3, Model 4, show that fixed effects of all control variable as well as random effects of variable Country continue to be highly significant (p < 0.001). They additionally show that age and education are significant predictors of innovation. As postulated, age has a negative effect and education has a positive effect. However, they also show that per capita gross national product (GNP) is not a significant predictor of entrepreneurial innovation. This means that H1 and H2 are supported (p < 0.001). However, H3 is not supported.

MLM with interaction variables
Finally, we enter our interaction variables in the analysis as below:

\[ I = \gamma_0 + \gamma_{opportunity} + \gamma_{suskil} + \gamma_{nff} + \gamma_{gender} + \gamma_{age} + \gamma_{edu} + \gamma_{NI} + \gamma_{(age*edu)} + \gamma_{(NI*age)} + \gamma_{(NI*edu)} + \mu_{C + \varepsilon} \]

The results of this model, summarized in Table 3, Model 5, show that fixed effects of all control variables, that of predictors, age and education, as well as random effects of variable Country continue to be highly significant. They also show that per capita GNI negatively influences the relationship of age with innovation (p < 0.05) and it positively influences relationship of education with innovation (p < 0.001), as postulated. However, it shows that age does not influence the relationship education of with innovation. This means that H3a (p < 0.001) and H3b (p < 0.05) are supported but H2a is rejected.

Local effect size
To determine the magnitude of influence captured by MLM, we use the equation below:

\[ \left( \sigma^2 \text{ null model} - \sigma^2 \text{ Model 5} \right) / \left( \sigma^2 \text{ null model} \right) \]

The Null model includes only the general intercept and no random effects, control variables, or predictors. The equation above therefore, captures the total effect size, which is 10%.

To know what part of this 10% variance is explained by our predictors, we use the equation below:

\[ \left( \sigma^2 \text{ Model 3} + \sigma^2 \text{ Model 3} - \sigma^2 \text{ Model 5} + \sigma^2 \text{ Model 5} \right) / \left( \sigma^2 \text{ Model 3} + \sigma^2 \text{ Model 5} \right) \]

This shows that 2% out of the total 10% variance in innovation is accounted for by the predictors.

Model fit
To check the improvements in model fit at successive stages of analysis, we compare -2 log likelihood (-2LL) ratios where smaller values are indicative of better fit of the model to the data. Subtracting -2LL deviance of Model 2 from that of Model 1, we find a positive difference of +18136 (p < 0.001), indicating a better fit of Model 2 than Model 1. The difference in -2LL between Model 3 and Model 2 is +39390, between Model 4 and Model 3 it is +6823, and between Model 5 and Model 4 it is +43. This means that, at each stage of analysis, the fitness of data to the model has improved.

Discussion and Conclusions
We discover that, at the individual level, being young and recently educated are significant predictors of entrepreneurial innovation whereas, at the societal level, national wealth dampens the negative effect of age on innovation and heightens the positive effect of education on it. Our work, thus, extends the literature on the relationship between age and innovation by showing that younger entrepreneurs are more innovative and, by controlling for education, it establishes that this result is not as influenced by education as thought previously (Frosch, 2011).

We also find empirical support for our earlier argument that the cause of failure of previous research to extend human capital theory to innovation (Delgado-Verde et al., 2016; Marvel & Lumpkin, 2007) is due to the inclusion of experience as a measure of human capital. Our work clarifies that it is only knowledge reflected in education —and not experience, echoed by age —that positively influences innovation. This finding is consistent with a significant part of previous research (Colombo et al., 2017; Crespo & Crespo, 2016; Miguelez et al., 2011; Rupieta & Backes-Gellner, 2017; Teixeira & Fortuna, 2010).

Our interaction results show that, notwithstanding their relative higher average age, the ability of entrepreneurs in developed countries to utilize their education for innovation is enhanced by the wealth of their nations, and we argue that this “wealth effect” operates through the mechanism of differential quality of national innovation support systems (Albuquerque et al., 2015; Lundvall, 2008; Watkins et al., 2015). As a result, entrepreneurs in richer countries have better
Human Capital, Its Constituents, and Entrepreneurial Innovation
Vijay Vyas and Renuka Vyas

innovation outcomes as national wealth accentuates the positive effect of education on innovation and dampens the negative effect of age on it.

Limitations
The variable age used in our work is chronological age, which “is best conceived as a proxy for true mechanistic changes that influence cognition across time” (MacDonald et al., 2011). As innovation needs “strong analytical thinkers”, individuals with high cognitive ability (De Visser et al., 2014), chronological age only approximates the true changes that occur over time in an individual’s ability to innovate. We have also posited linear relationships in our conceptual model. However, curvilinear effects of age (Jones, 2010) and national income on innovation are more plausible. The variable innovation in our analysis is not an objective measure but is computed from entrepreneurs’ self-reported responses to innovation-related questions. Finally, MLM has its own set of limitations that affect all studies that use this procedure including this research (González-Romá & Hernández, 2017). However, one specific limitation of MLM that affects studies with small datasets is not applicable in our case as both the number of groups (countries) and number of observations in each group are very large.

Contributions
We contribute to human capital theory by making a conceptual and empirical case against the use of work experience as a constituent of human capital. We explain the cause of counterintuitive and conflicting evidence in extant research on influence of human capital on innovation and suggest a path for its resolution. By using MLM, we contribute to the adoption of more robust methodological handling of GEM data. Using one of the largest available datasets, we carry out the first exploration of effect of entrepreneur age on innovation. We also theorize and test a novel set of moderating effects on innovation.

Implications for practice and future research directions
Given the disparities in educational provision between countries and the nexus among education, innovation, and economic prosperity, it is obvious from our findings that poorer countries should make investment in education their top priority. As demographic ageing has not yet set in, in these countries, this appears to be the straightest path to prosperity.

Though all developed countries perceive international students as a key part of their intangible exports, not all allow them the opportunity to settle down. Adverse innovation implications of this policy are highlighted by this work. Its converse ramification for the less developed countries such as India and China, from where the largest number of international students originate, however, is that they are losing a potential source of innovation, their competitiveness, and future growth in this process, and they would gain by improving the quality of their educational delivery as well as by extending it.

We also hope that this work generates more conceptual debate and further research on composition of human capital. As this study is based on data that is predominantly of very small enterprises (Schott & Jensen, 2016), studies using multi-country data of larger organizations should provide a complementary perspective to this scrutiny.

References
Belso-Martinez, J. A., Molina-Morales. F. X., & Mas-
Human Capital, Its Constituents, and Entrepreneurial Innovation

Vijay Vyas and Renuka Vyas


timreview.ca
Human Capital, Its Constituents, and Entrepreneurial Innovation

Vijay Vyas and Renuka Vyas

https://doi.org/10.1016/j.ibusvent.2005.04.003


Rupietta, C., & Backes-Gellner, U. 2017. High Quality Workplace Training and Innovation in Highly Developed Countries (No. 0074). Zurich, Switzerland: University of Zurich, Department of Business Administration (IBW).


Human Capital, Its Constituents, and Entrepreneurial Innovation

Vijay Vyas and Renuka Vyas


About the Authors

Vijay Vyas is Senior Lecturer in Entrepreneurship & Enterprise at the Faculty of Business & Law in University of Portsmouth in the United Kingdom. He holds a PhD from Edinburgh Napier University. He has been a Professor of Business Economics at the MS University in India and a visiting Professor in Entrepreneurship at Lancaster University in UK. He is the course director of MSc Innovation Management & Entrepreneurship at University of Portsmouth.

Renuka Vyas is PhD Research Scholar at Cardiff University in the United Kingdom. She holds a master’s degree in Social Research with a distinction from Birkbeck College, University of London, and a master’s in Economics from MS University of Baroda in India. She has been a Senior Lecturer in Economics at a Gujarat University college and a visiting Faculty in Entrepreneurship & Small Business Management at a Bhavnagar University Institute, both in India.


Keywords: age, education, work experience, national income, human capital, innovation, multi-level