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ABSTRACT

The role of human capital in shaping cross-national economic performance is well-understood. But human capital is an indirect measure of skill, based on educational attainment. We introduce and test a more direct measure of skill, based on work that is actually performed, measured by occupation. Recent empirical studies have shown that such occupational "classes" play an important role in regional economic performance, out-performing human capital in some cases. We develop a measure of occupational skill and examine its relation to in cross-national economic performance. We explicitly compare this measure to conventional measures of human capital (based on educational attainment) through formal models of economic performance for 55 to 78 countries, using three measures of economic performance – economic output (GDP per capita), productivity (total factor productivity) and innovative performance (patents). The results confirm the hypothesis, indicating that our occupation-based measure closely is associated with all three measures of economic performance and also that it consistently performs better than human capital in these models.

INTRODUCTION

The role of human capital in shaping economic growth is well-established. Romer (1986) and Lucas (1988) provide compelling theoretical reasons why knowledge accumulation is a central factor in economic growth. Lucas, inspired by Jacobs (1969), argues that knowledge and creative capabilities are key underlying mechanisms of economic growth, human capital externalities and concentration in cities. Economists and other social scientists have argued that the effect of human capital has to do with a shift in the nature of economies from an industrial or manufacturing base to a post-industrial or knowledge base (Machlup, 1962; Bell, 1973, 1976; Drucker, 1993).

A number of now classic studies (Barro, 1991; Becker, 1993; Barro and Lee, 1997) empirically document the effect of human capital on productivity, earnings and economic growth within and across nations. The role of human capital on economic growth has also been shown in models of regional growth. Several studies (Rauch 1993; Simon and Nardinelli 1996; Simon 1998; Berry and Glaeser, 2005) find strong empirical evidence of the role of human capital in the growth of US regions.

But human capital, at bottom, is a proximate measure for skill. Recent research, much of it in urban economics and regional science, contends that occupations provide a more robust measure of skill, by providing a direct measure of the work people actually perform. Several regional-level studies finds occupational measures to be closely associated with regional economic performance (Florida, 2002; Markusen, 2004; Marlet and Van Woerkens, 2004; Florida et al, 2008). Marlet and Van Woerkens (2004) provide empirical proof that both human capital and creative occupations (including science, technology, the arts, media and professions) predict employment growth in Dutch regions, but that the occupational measure is relatively stronger than human capital in explanatory value.

This paper tests a simple hypothesis. It argues that occupation plays a fundamental role, in cross-national economic performance. Providing a more direct measure of skill than education, we argue that our occupational measure should both predict cross-national variation in economic performance, and also outperform conventional human capital in doing so.

Our research tests this hypothesis through a series of formal models of economic performance for 55 to 78 countries. Our models compare occupations and human capital measures across three standard measures of economic performance – economic output (GDP per capita), productivity (total factor productivity) and innovative performance (patents).

The findings of the empirical analysis confirm the hypothesis. Occupation is closely related to cross-national economic performance; and it consistently outperforms educational measures of human capital in our models.

1. CONCEPTS AND THEORY

The role of human capital in shaping economic growth is well-established. Nelson and Phelps (1966) examined the impact of human capital on the national absorptive capacity of new ideas and new technologies, which they found affects the ability of leading nations to catch up. Becker (1993) revealed a link between education and productivity levels at the individual level, which ultimately affects the wage level. Human capital is included as a variable in many endogenous growth models. Romer (1986, 1990) considers human capital to be a key factor behind innovation and technological progress; a factor that can be influenced through investments in education. Building on Romer's work, Krugman (1991) and Grossman and Helpman (1991) have stressed the role of local knowledge spillovers in economic growth. In detailed cross-national empirical studies, Barro (1991, 2001) found clear evidence of the effect of educational attainment on national growth levels, using data from more than 100 countries from 1965-1995.

The importance of human capital has also been a key finding in regional economics. Lucas (1988) examined the impact of investments in human capital on growth, and stressed that the accumulation of human capital is a social activity involving group interactions, whereas accumulation of physical capital is not. These group interactions take place in cities, they give rise to human capital externalities, and in the end they are a key mechanism of economic growth. Lucas draws upon Jacobs (1969), who earlier argued that knowledge and creative capabilities are key mechanisms of economic growth; human capital externalities and concentration in cities. Extending Lucas' reasoning about human capital as a social good with human capital externalities, Rauch (1993) suggested that human capital should earn higher wages in human capital rich regions than in human capital poor ones. Simon and Nardinelli (1996) focused on the role of cities as arenas for face-to-face interaction for human capital and examined the impact it has on regional economic growth between 1861 and 1961. Their work is rare in that it uses occupational classes as proxies for human capital, rather than the educational levels of the population. Simon (1998) as well as Glaeser et al. (1995) showed the regional human capital effect on employment growth, and Berry and Glaeser (2005) examined the path dependency of the distribution of human capital across cities over time.

Recent research in regional science and urban economics has argued that occupations provide a better, more direct measure of skill than educational human capital. A series of empirical studies have found that occupations can be efficiently grouped into large classes and that these classes tend to outperform standard human capital measures in explaining differences in levels of regional development (Florida, 2002; Marlet and Van Woerkens, 2004).

Previous research identifies three broad groupings or "classes" of occupations (Machlup, 1962; Bell, 1973, 1976; Wright, 1982, 1990; Drucker, 1993; Florida, 2002; Florida and Martin, 2009). The first type is *routine physical work* which includes occupations in manufacturing, production, transportation and construction. Occupations such as derrick operators, firefighters, electricians, mechanics and roofers require high levels of physical skills such as dexterity, coordination, and strength), but lower levels of cognitive problem-solving skills. *Routine service occupations* are the second type of work; they include jobs in food preparation and food-service-related occupations, building and grounds cleaning and maintenance, personal care and service, low-end sales, office and administrative support, community and social services, and protective services. These occupations are also more routine and require low levels of analytical, cognitive or problem solving skills. The third type of work is work that depends on knowledge, creativity and cognitive skill. It is referred to variously in previous studies as *knowledge, cognitive, professional and/or creative work* (Machlup, 1962; Bell1973, 1976; Wright, 1982, 1990; Drucker, 1993; Brint, 1994; Florida, 2002).

Based on this, we group occupations into three clusters or classes in our analysis; Routine Physical, Routine Service, and Knowledge-Professional-Creative (KPC). This follows the tripartite occupational scheme advanced by Florida (2002) to some degree, with adaptation and revision based on more recent research and the structure of cross-national data. It is worth noting that while there has been some debate over elements of Florida's work - particularly his findings regarding the relationship between openness, human capital and economic performance, there is an emerging consensus over this occupational classification system. Glaeser (2004) argued that the creative class explains little that is not already explained by human capital measures. However, McGranahan and Wojan (2007) made minor adjustments to the creative class measure and evaluated its strength in relation to more traditional human capital, and found it more robust in explaining regional employment growth. Marlets and Van Woerken (2004) found that the creative class would explain employment growth more than educational levels in Dutch regions. Florida et al. (2008) systematically tested the role of human capital and creative occupations against several measures of regional economic performance, and found that human capital is more closely associated with incomes, while occupations are more closely associated with wages.

Our research is straightforward; this paper aims to examine the role of occupational or occupational skill on cross-national economic performance. While the importance of educational human capital has been emphasized in economic theory and documented in empirical studies, the role of occupation skill has not been tested in cross-national studies. We argue that occupation provides a more direct measure of skill, and as such it is likely to outperform conventional education-based measures of human capital in predicting cross-national economic performance.

We test this proposition with formal models of economic performance for 55 to 78 countries. We compare the effects of occupational and educational skill (human capital) on three widely used economic performance measures – economic output (GDP per capita), productivity (total factor productivity) and innovative performance (patents).

2. METHODOLOGY

We focus our analysis on the relationship between KPC occupations and cross-national economic performance. Taking into account Glaeser's (2004) contention that KPC occupations and human capital may reflect the same underlying skill effect, we also include standard human capital measures in our models to control for this. In addition, we also let education explain the share of KPC occupations, to examine how much that is left unexplained in a straightforward regression. Our analysis is designed to examine the relative strength of KPC occupations and educational human capital in explaining three measures of economic performance - GDP per Capita, Total Factor Productivity (TFP) and Patents. We also control for country/continental specific fixed effects for OECD, EU15 and Asia, as well as physical capital and investments in R&D.

We utilize data from a number of different data sources across 55-78 countries. Unfortunately, some of the data is not available all countries for every year, so the number of observations varies to some degree. In order to increase the number of observations, and also to smooth out any extreme values, we use the average values for these variables (as indicated below). We excluded African countries from the data set for two reasons: data scarcity and because they constitute extreme outliers which distort the overall outcome.

VARIABLES

Dependent variables:

We employ three dependent variables in our analysis, as noted above; a measure of output per capita (GDP per capita), productivity (Total Factor Productivity), and innovative performance (patents per capita);

GDP per Capita: GDP per capita is a standard measure of economic performance. This measure is based on 2005 data from the World Development Indicators.

Total Factor Productivity: Ever since Solow (1956), it has been established that long-run economic growth is determined by the "residual factor" or Total Factor Productivity (TFP). Easterly and Levine (2001) have provided compelling evidence that cross-country differences in both the level and growth rate of GDP per capita are explained by TFP, not factor accumulation. Based on work by Gollin (2002) we could expect capital to be approximately 1/3 and labor to account for 2/3. We then calculate the TFP as the residual (log scale): $\ln TFP = \ln Y - \frac{1}{3}\ln K - \frac{2}{3}\ln L$

The data is from the World Development Indicators and is for 2006.

Patents: Patents are a commonly used measure of technological innovation and innovative performance (e.g. Jaffe, 1986; Audretsch and Feldman, 1996; Jaffe and Trajtenberg, 2002). We employ patent data from two different sources: the US Patent and Trademark Office (USPTO) and the World Intellectual Property Office (WIPO). Inventors from around the world file for patent protection in the United States, and the USPTO tracks the origin of the inventor, we can count the number of *granted* US patents for each nation in the world. This file can undercount (sometimes radically) inventions in other countries due to the fact that not every inventor files for a US patent. Therefore, we also include the number of patents reported to the WIPO by each national patent office. Both variables are expressed as patents per capita. The USPTO data is for year 2001-2008, while the WIPO data is for year 2000-2007.

Independent Variables:

We employ several classes of independent variables.

Human Capital: We employ two standard measures of human capital;

Barro Lee Human Capital**:** The first is the well-known Barro and Lee measure of human capital (Barro and Lee, 2001), which measures the population's average number of years in education.

WDI Human Capital**:** The second is based on the World Development Indicators Tertiary Education Enrollment data, which is defined as the share of the labor force with a tertiary diploma or degree. Tertiary education refers to training at a wide range of post-secondary education institutions, including technical and vocational schools, community colleges, and universities, which normally require as a minimum condition of admission the successful completion of education at the secondary level. Since these data are not reported for each country every year, we calculate an average for the reported numbers for the years 2001-2006.

Occupational Measures*:* We employ the following classification.

Knowledge-Professional-Creative (KPC) Occupations: Following previous research (Machlup, 1962; Drucker, 1993; Florida, 2002), KPC occupations are those that involve high levels of cognitive skill, complex problem solving, relatively autonomous decision-making, and independent judgment. KPC occupations include: computer science and mathematics; architecture, engineering; life, physical, and social science; education, training, and library science; arts and design work, entertainment, sports, and media; and professional and knowledge work occupations in management, business and finance, law, sales management, healthcare, and education,. The variable is measured as a share of the total employed labor force. The data is from the International Labor Organization. The data this variable is based on is not reported by each country annually; in order to increase the number of observations, we calculate an average for the reported numbers for the years 2001-2007.

Routine Physical Occupations: This group consists of occupations characterized by routine physical skill. It includes occupations in construction and extraction, installation, maintenance and repair, production, transportation and material moving occupations. The variable is measured as share of the regional labor force. The data is from the International Labor Organization. We calculate an average for the reported numbers for the years 2001-2007, to increase the number of observations.

Routine Service Occupations: This group consists of traditional and standard services (separate from more knowledge based services), such as food preparation and food-service-related occupations, building and grounds cleaning and maintenance, personal care and service, low-end sales, office and administrative support, community and social services, and protective services. This variable is measured as share of the total employed labor force. Routine service occupations are based on occupational data from the International Labor Organization. We calculate an average for the reported numbers for the years 2001-2007, to increase the number of observations.

Control variables: We use a variety of control variables in our analysis.

Physical Capital: Since GDP, as well as labor productivity, is a function of both capital and labor in the neoclassical context, we include a control variable for physical capital in our regressions for GDP per capita,. This measure is based on 2005 data from the World Development Indicators. However, since the number of observations is small, we will run this regression both with and without the physical capital control variable.

R&D Expenditure: Innovation, namely patent production, is a function not only of knowledge levels but also of the capital investments made in R&D (e.g. Jaffe, 1989, 2000). We include a control variable for R&D investments – measured as the R&D share of l GDP. This is based on 2005 data from the World Development Indicators. Since the number of observations for this variable is small, we perform regressions with and without this control variable.

We add three additional control (dummy) variables to the above measures, in order to control for fixed continent/country effects:

OECD: This dummy variable indicates if the country is an OECD member. This includes the following nations: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Portugal, Republic of Korea, Slovakia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States.

EU15: This dummy variable indicates if the country is one of the EU15 countries (before the extension of the number of EU member states). This includes Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

Asia: This dummy variable indicates if the country is located in Asia, and it includes the following nations: Armenia, Azerbaijan, Bangladesh, Cambodia, China, Georgia, Indonesia, Iran, Israel, Japan, Kazakhstan, Kyrgyzstan, Macau, Malaysia, Maldives, Pakistan, Philippines, Republic of Korea, Russian Federation, Saudi Arabia, Singapore, Sri Lanka, Syrian Arab Republic, Thailand, Turkey and Vietnam. We are well aware of the variance in economic performance of the Asian countries, but expect this difference to partly be captured by the OECD variable.

Descriptive statistics for the variables are summarized in Table 1.

(Table 1 about here)

Since the data is not available for all the nations, we used average levels over a number of years for some of the variables as described above. The maximum amount of nations we have is 116 (for the occupational classes) and the minimum is 69 (for the Barro and Lee human capital measure). We do not employ all the variables simultaneously, but substitute them where suitable to check for robustness.

Table 2 provides a simple correlation matrix for our main variables. The KPC measure is significantly correlated with GDP per capita (0.644), TFP (0.715), and both patent measures, USPTO (0.731) and WIPO (0.774). It is also correlated with Barro Lee human capital (0.690) and WDI human capital (0.558).

Barro Lee human capital is significantly correlated with economic performance:
0.747 with GDP per capita, 0.733 with TFP, 0.731 with USPTO patents and 0.747 with WIPO patents. We find significant and positive relationships between WDI human capital and each of the economic performance measures: 0.516 to GDP per capita, 0.590 to TFP, and 0.668 to UPTO patents and 0.593 to WIPO patents. Appendix 1 provides scatterplots which illustrate these relationships.

(Table 2 about here)

We conduct two simple regressions to test whether KPC and human capital variables include essentially the same information. In the first, we let Barro Lee human capital explain KPC; the second does the same for WDI human capital. While the results from the first regression shows a strong relationship (coefficient of 1.183 and a t-value of 7.794) between Barro Lee human capital and KPC, more than half of the variation remains unexplained (R2 is 0.476). While Barro Lee human capital partly explains KPC, the two variables do clearly not contain exactly the same type of information. In the second regression, when we let WDI human capital explain KPC, the coefficient is 0.332 and significant (t-value of 6.550), but the R2 value remains only 0.311. This means that WDI human capital explains less of the KPC than Barro Lee human capital with almost 70 percent of the relationship left unexplained.

3. REGRESSION FINDINGS

We now turn the results of our economic performance regressions. We focus on the standardized beta-coefficients to examine the relative strength of the variables. Since we are using a cross-sectional data set, we cannot analyze changes over time. We examine the effects of KPC and human capital on three measures of economic performance: GDP per capita, TFP, and patents per capita. For all regressions, we also control for other occupational groups - Routine Physical and Routine Service - and country fixed effects.

Explaining GDP per Capita

We start with the regressions for GDP per capita. We use the same regression twice for each of the human capital variables. While the Barro Lee human capital can be expected to be more correlated with KPC, the number of observations is smaller (Table 3). To check the robustness of the regression and to increase the number of observations, the second regression (Table 4) uses WDI human capital.

(Table 3 about here)

(Table 4 about here)

From the regression results (Table 3) we can see that two occupational groupings–- KPC and Routine Service - are significantly and positively related to GDP per Capita. Barro Lee human capital is also positive and significant in relation to the GDP per Capita, but the standardized beta value (St. β) tells us that it has less impact than either KPC or Routine Service (0.232 versus 0.386 and 0.287). The low VIF values (all below 2.4) exclude that the average years of education and KPC include the same information. The variable for Routine Physical occupations has a negative and significant impact at the 0.05 level (St. β of -0.144 and a t-value of -2.268). Further, we find a positive and significant effect from the OECD fixed effect dummy, telling us that if the nation is an OECD country that will add to the explanatory value of the national GDP per Capita value. There is also a positive and significant effect from being one of the EU15 countries at the 0.1 level. Taken together, these variables will explain around 85 percent of the variation (with a R2 of approximately 0.869).

We now move on to the second regression (Table 4) where we use the WDI measure of human capital. Two occupational variables – KPC and Routine Service - are again highly significant and positive (St. β of 0.404 and 0.418). The Routine Physical variable has now lost significance and the human capital variable is no longer significant. Among the fixed country or continent variables, only OECD stays significant. Taken together, these variables explain approximately 76 percent of the variation (the R2 is 0.786). Again, we rule out any collinearity problems, since the VIF values are at an acceptable level.

It is important to note that the both the KPC and Routine Service variables outperform each of the human capital measures in explaining GDP per capita. This result leads us to conclude that occupational skill better explains GDP per capita than educational human capital.

Since we normally assume GDP per capita to be a function of both labor and physical capital, we also add a regression controlling for physical capital (see Appendix 2). The variable is insignificant in the regression with Barro Lee human capital, and only significant at the 0.1 level in the regression with WDI human capital variable. The KPC and human capital variables stay fairly robust. However, the control for physical capital has some effect on the Routine Service coefficient which becomes slightly weaker when physical capital is included. Including this physical capital variable only has minor effects on the R2 value in both regressions.

Explaining Total Factor Productivity

We now move on to our regression analysis of TFP, letting the same independent variables explain national TFP levels (Table 5 and 6).

(Table 5 about here)

(Table 6 about here)

In our first regression (Table 5), human capital is represented by the Barro Lee measure. The results show that KPC is the most important factor in explaining TFP, with a standardized beta value of 0.414 (t-value of 5.652). This is followed by the Barro Lee variable (St. β of 0.208, and a t-value equal to 3.740). Next is Routine Service occupations which is also positive and significant (St. β coefficient of 0.208, and a t-value of 3.630). Both the OECD and EU15 control variables are positive and significant, adding further to the explanatory power of our regression, which generates a R2 of 0.886.

When the WDI human capital measure replaces the Barro Lee measure, the human capital measure becomes insignificant and we get an evaluation of Routine Service variable strength (with a standardized beta coefficient of 0.327, and a t-value of 4.600). Here again, KPC tends to most strongly explain total factor productivity, with a standardized beta value of 0.434 (t-value 4.987). Among the fixed effect control variables, only the OECD factor is significantly related to the total factor productivity. Taken together, the regression generates a R2 value of 0.798.

Again, the KPC measure outperforms both human capital variables in explaining TFP. Also, the low VIF values rule out any collinearity problems between KPC and the human capital variables.

Explaining Patented Innovations

We now turn to patents as a measure of innovative performance. We execute two regressions using the same independent variables, and let them explain patent production. The first two regressions (Tables 7 and 8) use patents granted in the US as a dependent variable. We also perform the regression, using patents reported by WIPO (Tables 9 and 10. We again test for the relative importance of occupational skill versus educational human capital.

(Table 7 about here)

(Table 8 about here)

The results of the regressions (Tables 7 and 8) show that occupational class explains much of the variation in patents. In the first regression, Barro Lee human capital has a strong influence (St. β of 0.330, t-value of 4.124), but it is again outperformed by the KPC (St. β of 0.415, t-value of 4.692). Routine Service is also positive and significant (St. β of 0.227, t-value of 3.736), while Routine Physical is negative and significant at the 0.05 level in this context (St. β of -0.131, t-value of -2.073), The larger nation's share of Routine Physical occupations, the less innovative we can expect the nation to be. Among the fixed effect control variables only EU15 comes out as significant at the 0.1 level. In total the regression generates an R2 value of 0.859.

When we substitute WDI human capital, the KPC still has the strongest influence (St. β of 0.469, t-value of 5.164), while WDI human capital looses significance. We also, once more, see a relative increase in strength of Routine Service. Among the fixed effect control variables the OECD variable is positive and significant at the 0.05 level, and the Asia variable positive and significant at the 0.1 level and the R2 value is 0.798.

We repeat the regressions controlling for the national share of R&D expenditure (see Appendix 2). This variable is significant in both regressions, and increases the R2 value approximately by 0.3-0.5. It has its biggest effect on human capital variables, particularly the Barro Lee variable, which now only is significant at the 0.5 level. The KPC variable remains s relatively stronger than the human capital variables in both regressions.

The next regressions (Tables 9 and 10) substitute use WIPO patents as the dependent variable.

(Table 9 about here)

(Table 10 about here)

The results from these regressions (Table 9) are fairly consistent with the results in of USPTO regressions. Barro Lee human capital remains significant (St. β of 0.255, t-value of 2.431) but it is weaker than the KPC variable (St. β of 0.493, and a t-value of 4.227). The variable for Routine Service occupations loses significance while that for Routine Physical occupations becomes even stronger and negatively related to national patenting. None of the fixed effect variables emerges as significant, and the regression generates an R2 of 0.761, which is somewhat weaker than when we used granted USPTO patents as dependent.

The final regression (Table 10) includes the WDI human capital variable. The results are consistent with those in Table 9. WDI human capital is now significant, which differs from the GDP per Capita, TFP and USPTO patent regressions. However, KPC still outperforms it (β of 0.458 versus 0.320, and a t-value of 4.084 versus 3.028). The variable for Routine Service is still insignificantly related to patent production, and that for Routine Physical remains negative and significant (now at the 0.05 level). The OECD variable is the only of the fixed effect variable that is significant (at the 0.05 level). The R2 is 0.747, which is approximately at the same level as for the regression in Table 9, when average years of education were used instead of tertiary education enrollment.

Once again, when we include the control variable for R&D expenditure, it is highly significant and increases the R2 values with or is this by approximately 0.5 (see Appendix 2). The variables affected the most by this control variable are the human capital measures. The Barro Lee human capital no longer stays significant, and the WDI human capital only is significant at the 0.1 level. The KPC variable stays significant at the 0.01 level in both regressions.

4. CONCLUSIONS

Our research has examined the role of occupational skill in cross-national economic performance. We started from the premise that occupation provides a more direct measure of skill than education. We directly tested the role of occupational skill as compared to human capital in regressions models of economic performance for a cross-section of countries.

Our findings confirm our hypotheses. Our main occupational variable – KPC – a measure of knowledge, creative and professional occupations - is both significantly related to cross-national economic performance and consistently outperforms conventional measures of human capital in our models, using three measures of economic performance – economic output (GDP per capita), productivity (total factor productivity) and innovative performance (patents). These findings are in line with e.g. earlier work by Marlets and Van Woerkers (2004), McGranahan and Wojan (2007) or Florida et al (2008). Our findings also contrast with Glaeser's (2004) contention that occupational skill and human capital are essentially measuring the same underlying skill factor. We find that while educational and occupational skill are correlated, our analysis shows they are not the same thing. Our regressions between KPC and the two human capital variables leave much of the variance unexplained, with R2 values of 0.476 and 0.311 respectively. Related work shows that while 88 percent of college educated workers work in KPC occupations in Sweden, only 26 percent of KPC workers have college educations (Mellander, 2009).

A second occupational variable - Routine Service occupations – is also related to economic performance. This is likely to be an artifact of economic structure. Economies with larger KPC sectors have greater demand for Routine Service, and thus larger concentrations of those occupations. The two variables are correlated (0.432). This is part and parcel of the general economic development process as more advanced economies move away from traditional industrial sectors and Routine Physical occupations and toward higher concentrations of KPC and Routine Service occupations.

Routine Physical occupations are either insignificant or negatively associated with economic performance. This again appears to be part and parcel of the more general process of economic development. Nations with large manufacturing and production sectors and large shares of routine physical occupations lag on economic output, TFP and innovation.

Generally speaking our findings suggest that occupations and occupational skill are important factors in cross-national economic performance, outperforming the conventional human capital measures in our analyses. We want to encourage future research using occupational measures and further clarifying the relationship between these two measures of skill based on education and work.

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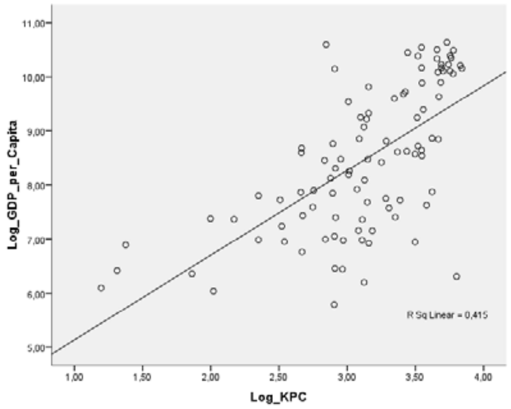
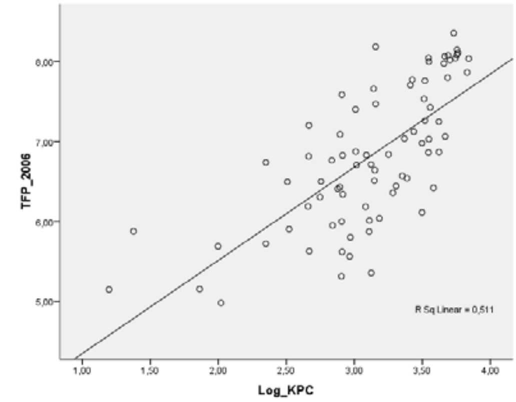
APPENDIX 1:

Scatter-Plots for GDP per Capita	**Scatter-Plots for Total Factor Productivity**



KPC



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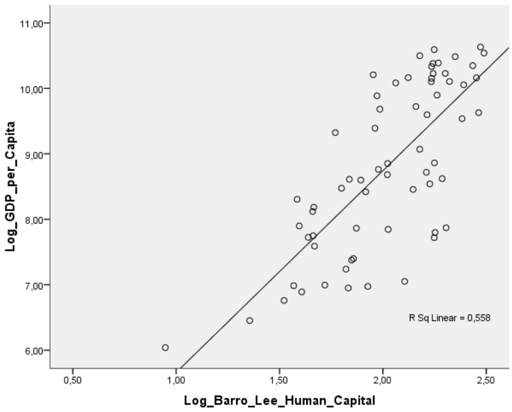
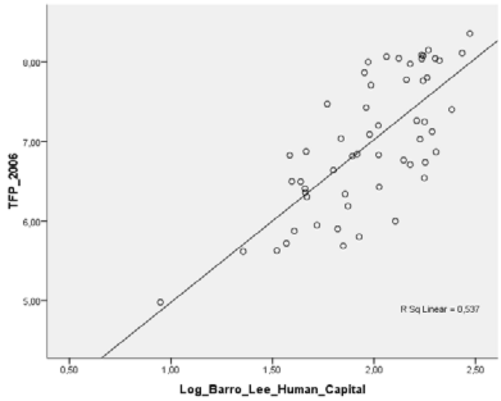


Barro Lee Human Capital



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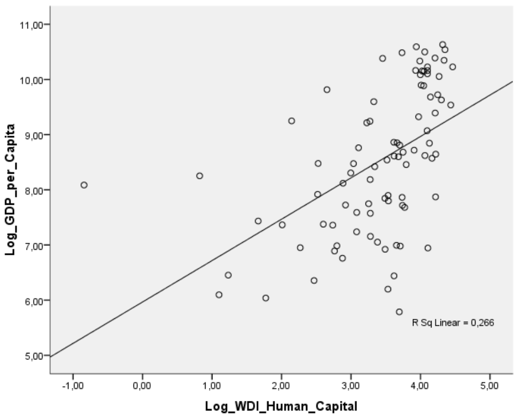
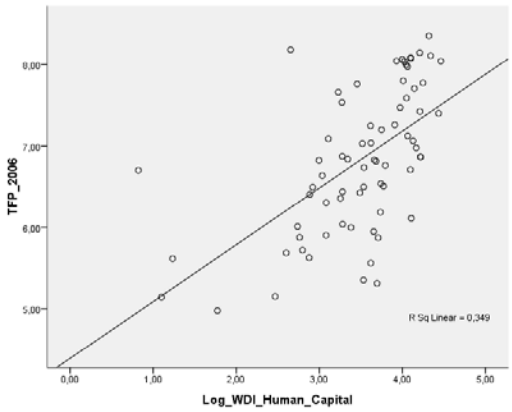


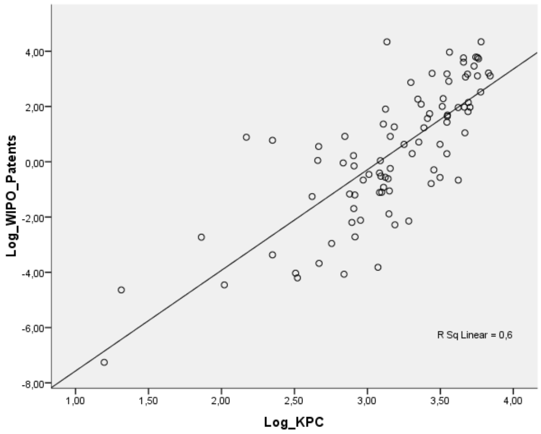
WDI Human Capital



WDI Human Capital

Innovation Scatter-Plots

<u>WIPO Patents per Capita</u>	**<u>USPTO Patents per Capita</u>**



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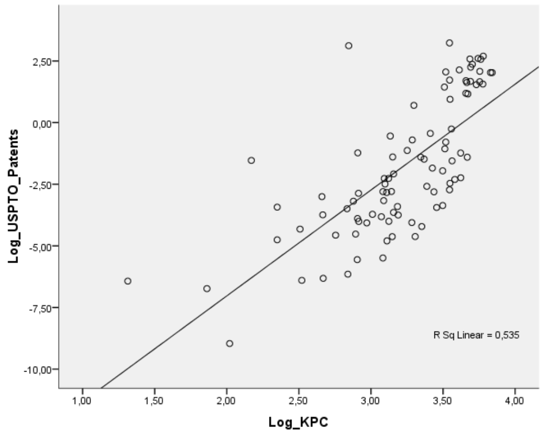

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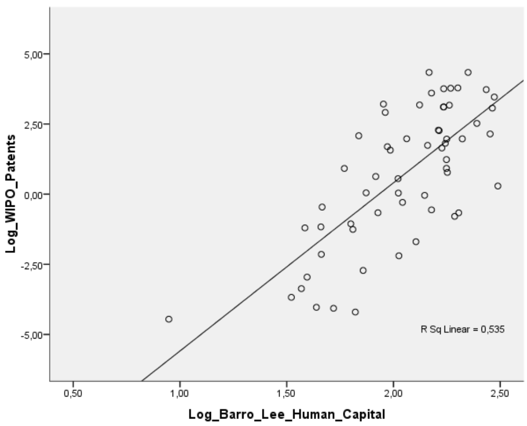
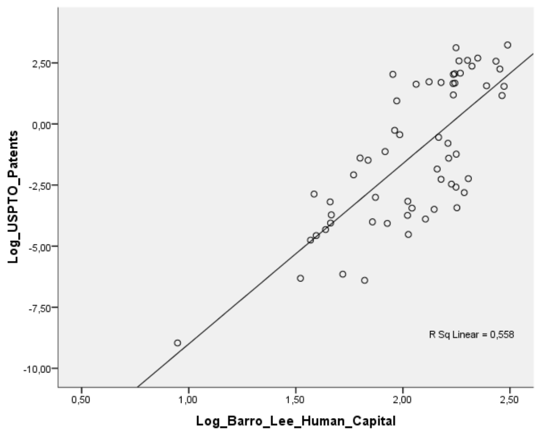


Barro Lee Human Capital



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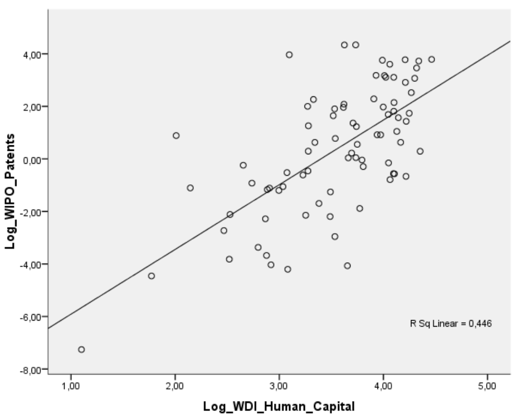

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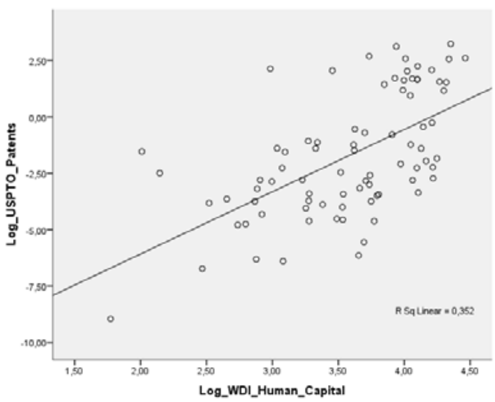

WDI Human Capital

APPENDIX 2:

Table 3 and 4, controlling for physical capital

Model	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	2.590	2.175		1.191	.240		
KPC	.933	.187	.404	4.985	.000	.440	2.274
Barro Lee Human Capital	.892	.310	.219	2.877	.006	.497	2.014
Routine Service	.895	.243	.232	3.689	.001	.730	1.370
Routine Physical	-.665	.275	-.154	-2.420	.020	.716	1.396
Physical Capital	.025	.060	.033	.414	.681	.452	2.213
OECD	.530	.228	.208	2.322	.025	.359	2.787
EU15	.311	.255	.108	1.220	.229	.366	2.732
ASIA	.003	.207	.001	.013	.990	.530	1.888
R2	0.873						
Obs	52						

Model	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	-.072	1.714		-.042	.967		
KPC	.930	.228	.397	4.084	.000	.425	2.352
WDI Human Capital	.065	.157	.039	.414	.680	.448	2.233
Routine Service	1.258	.269	.365	4.671	.000	.659	1.517
Routine Physical	-.339	.278	-.088	-1.221	.227	.765	1.307
Physical Capital	.103	.057	.150	1.806	.076	.584	1.713
OECD	.623	.292	.224	2.132	.037	.363	2.754
EU15	.270	.327	.083	.826	.412	.398	2.511
ASIA	.023	.229	.009	.103	.919	.577	1.732
R2	0.779						
Obs	63						

Table 7 and 8, controlling for national R&D expenditure

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
(Constant)	-10.450	4.523		-2.310	.026		
KPC	1.966	.548	.294	3.586	.001	.385	2.600
Barro Lee Human Capital	1.717	.814	.157	2.110	.041	.465	2.148
Routine Service	1.542	.640	.149	2.410	.020	.670	1.492
Routine Physical	-1.638	.710	-.148	-2.308	.026	.630	1.587
R&D Expenditure	.794	.226	.358	3.505	.001	.247	4.051
OECD	.135	.473	.024	.285	.777	.359	2.788
EU15	.760	.434	.125	1.750	.087	.505	1.979
ASIA	.743	.481	.100	1.543	.130	.615	1.627
R2	0.887						
Obs	52						

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
(Constant)	-9.172	3.424		-2.678	.010		
KPC	2.075	.540	.320	3.840	.000	.393	2.548
WDI Human Capital	-.334	.425	-.061	-.785	.436	.454	2.204
Routine Service	2.121	.492	.263	4.315	.000	.732	1.367
Routine Physical	-1.298	.514	-.147	-2.524	.015	.807	1.239
R&D Expenditure	.984	.206	.428	4.782	.000	.340	2.945
OECD	.517	.496	.092	1.043	.302	.353	2.832
EU15	.669	.480	.104	1.395	.169	.494	2.024
ASIA	.616	.423	.093	1.458	.151	.668	1.496
R2	0.856						
Obs	61						

Table 9 and 10, controlling for national R&D expenditure

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
(Constant)	5.128	4.794		1.070	.291		
KPC	1.848	.577	.345	3.201	.003	.379	2.637
Barro Lee Human Capital	.384	.857	.044	.448	.656	.460	2.173
Routine Service	-1.589	.674	-.192	-2.357	.023	.667	1.499
Routine Physical	-1.655	.741	-.187	-2.234	.031	.630	1.588
R&D Expenditure	.826	.237	.467	3.489	.001	.246	4.065
OECD	.384	.502	.085	.765	.448	.354	2.826
EU15	-.326	.453	-.067	-.719	.476	.509	1.963
ASIA	-.672	.503	-.113	-1.337	.188	.617	1.622
R2	0.810						
Obs	51						

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
(Constant)	-3.273	2.698		-1.213	.230		
KPC	1.995	.523	.430	3.817	.000	.312	3.204
WDI Human Capital	.694	.409	.180	1.695	.096	.350	2.861
Routine Service	-.481	.493	-.075	-.976	.333	.676	1.480
Routine Physical	-1.039	.477	-.148	-2.177	.034	.859	1.164
R&D Expenditure	.486	.205	.261	2.368	.022	.326	3.070
OECD	.789	.506	.167	1.560	.125	.346	2.893
EU15	-.351	.484	-.065	-.725	.472	.496	2.015
ASIA	-.108	.425	-.020	-.254	.801	.643	1.555
R2	0.791						
Obs	61						

Tables:

Table 1: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
GDP per Capita	98	326	41446	10260	11631
TFP	78	4.98	8.36	6.82	.878
WIPO Patents	106	.00	76.66	7.64	14.98
USPTO Patents	94	.00	25.35	2.36	4.80
KPC	116	3.31	46.57	26.16	10.56
Routine Service	116	3.13	46.06	24.51	8.50
Routine Physical	116	10.35	74.49	34.95	10.53
Barro Lee Human Capital	69	2.58	12.05	7.89	2.16
WDI Human Capital	97	.43	86.74	38.11	21.40

Table2: Correlation Matrix for Occupation and d Human Capital Variables (logged relations)

Variables	**KPC**	**Barro- Lee Human Capital**	**WDI Human Capital**
Economic Variables			
GDP per Capita	0.644***	0.747***	0.516***
TFP	0.715***	0.733***	0.590***
WIPO Patents	0.774***	0.731***	0.668***
USPTO Patents	0.731***	0.747***	0.593***
Other Occupational Classes			
Routine service	0.423***	0.275**	0.337**
Routine physical	0.019	-0.250**	-0.105
Continent Dummies			
OECD	0.513***	0.556***	0.445***
EU15	0.429***	0.342***	0.361***
ASIA	-0.385***	-0.269**	-0.326***
Capital			
Physical Capital	0.204*	0.351***	0.364***
R&D Expenditure	0.630***	0.655***	0.652***

*** sign at the 0.01 level
** sign at the 0.05 level
* sign at the 0.1 level

Table 3: Regression Result for GDP per Capita with Barro Lee Human Capital included (logged variables)

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	2.300	1.362		1.689	.097		
KPC	.931	.179	.386	5.211	.000	.428	2.334
Barro Lee Human Capital	.957	.295	.232	3.245	.002	.460	2.173
Routine Service	1.120	.215	.287	5.204	.000	.774	1.293
Routine Physical	-.658	.250	-.144	-2.628	.011	.781	1.280
OECD	.503	.193	.196	2.614	.011	.418	2.393
EU15	.343	.201	.117	1.709	.093	.504	1.983
ASIA	.185	.176	.062	1.054	.297	.688	1.454
R2	.869						
Obs	63						

Table 4: Regression Result for GDP per Capita with WDI Human Capital included (logged variables)

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	1.386	1.204		1.151	.253		
KPC	.981	.182	.404	5.383	.000	.536	1.866
WDI Human Capital	.032	.103	.022	.307	.760	.612	1.633
Routine Service	1.452	.226	.418	6.429	.000	.716	1.397
Routine Physical	-.263	.240	-.066	-1.096	.277	.845	1.183
OECD	.793	.229	.285	3.454	.001	.444	2.254
EU15	.343	.258	.102	1.333	.187	.515	1.941
ASIA	.248	.199	.085	1.248	.216	.644	1.552
R2	.786						
Obs	78						

Table 5: Regression Result for Total Factor Productivity with Barro Lee Human Capital included (logged variables)

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
(Constant)	2.957	.900		3.286	.002		
KPC	.654	.116	.414	5.652	.000	.442	2.262
Barro Lee Human Capital	.707	.189	.254	3.740	.000	.516	1.937
Routine Service	.530	.146	.208	3.630	.001	.725	1.380
Routine Physical	-.370	.166	-.124	-2.233	.030	.772	1.296
OECD	.334	.130	.194	2.561	.014	.416	2.406
EU15	.312	.148	.158	2.105	.041	.423	2.366
ASIA	.005	.119	.003	.044	.965	.619	1.615
R2	.886	.869					
Obs	55						

Table 6 Regression Result for Total Factor Productivity with WDI Human Capital included (logged variables)

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
(Constant)	2.452	.803		3.052	.003		
KPC	.677	.136	.434	4.987	.000	.446	2.244
WDI Human Capital	.092	.097	.080	.950	.346	.475	2.106
Routine Service	.735	.160	.327	4.600	.000	.668	1.498
Routine Physical	-.153	.161	-.060	-.951	.346	.855	1.170
OECD	.504	.166	.265	3.026	.004	.439	2.279
EU15	.317	.197	.140	1.607	.113	.447	2.237
ASIA	.099	.139	.053	.716	.477	.616	1.624
R2	.798						
Obs	67						

Table 7: Regression Result for USPTO Granted Patents with Barro Lee Human Capital included (logged variables)

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	-20.402	4.205		-4.852	.000		
KPC	2.701	.576	.415	4.692	.000	.368	2.715
Barro Lee Human Capital	3.251	.788	.330	4.124	.000	.451	2.219
Routine Service	2.546	.681	.227	3.736	.000	.781	1.281
Routine Physical	-1.472	.710	-.131	-2.073	.043	.721	1.387
OECD	.536	.508	.090	1.055	.297	.394	2.541
EU15	.859	.503	.131	1.708	.094	.492	2.031
ASIA	1.304	.480	.168	2.717	.009	.756	1.323
R2	.859						
Obs	56						

Table 8: Regression Result for USPTO Granted Patents with WDI Human Capital included (logged variables)

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	-18.591	3.382		-5.498	.000		
KPC	2.995	.580	.469	5.164	.000	.402	2.486
WDI Human Capital	.663	.426	.131	1.555	.125	.470	2.128
Routine Service	2.432	.556	.288	4.376	.000	.765	1.308
Routine Physical	-1.029	.583	-.113	-1.765	.083	.813	1.230
OECD	1.354	.536	.229	2.527	.014	.405	2.469
EU15	.412	.570	.060	.722	.473	.485	2.061
ASIA	.820	.465	.122	1.762	.083	.696	1.436
R2	.798						
Obs	68						

Table 9: Regression Result for WIPO Patents with Barro Lee Human Capital included (logged variables)

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	-2.253	4.604		-.489	.627		
KPC	2.660	.629	.493	4.227	.000	.366	2.730
Barro Lee Human Capital	2.088	.859	.255	2.431	.019	.452	2.215
Routine Service	-.673	.745	-.072	-.904	.371	.783	1.276
Routine Physical	-2.291	.771	-.247	-2.969	.005	.721	1.387
OECD	.603	.562	.122	1.073	.289	.386	2.593
EU15	-.268	.547	-.049	-.490	.626	.496	2.018
ASIA	-.024	.522	-.004	-.046	.964	.757	1.320
R2	.761						
Obs	55						

Table 10: Regression Result for WIPO patents with WDI Human Capital included (logged variables)

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	-4.896	2.726		-1.796	.077		
KPC	2.252	.551	.458	4.084	.000	.330	3.030
WDI Human Capital	1.248	.412	.320	3.028	.004	.371	2.699
Routine Service	-.563	.539	-.080	-1.045	.300	.715	1.399
Routine Physical	-1.421	.533	-.187	-2.664	.010	.842	1.188
OECD	1.181	.523	.228	2.258	.028	.406	2.461
EU15	-.524	.558	-.087	-.940	.351	.486	2.059
ASIA	-.106	.453	-.018	-.233	.816	.675	1.482
R2	.747						
Obs	68						

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