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ABSTRACT

A longstanding research tradition assumes that endogenous technological development increases regional productivity. It has been assumed that measures of regional patenting activity or human capital are an adequate way to capture the endogenous creation of new ideas that result in productivity improvements. This process has been conceived as occurring in two stages. First, an invention or innovation is generated, and then it is developed and commercialized to create benefits for the individual or firm owning the idea. Typically these steps are combined into a single model of the "invention in/productivity out" variety. Using data on Gross Metropolitan Product per worker and on inventors, educational attainment, and creative workers (together with other important socio-economic controls), we unpack the model back to the two-step process and use a SEM modeling framework to investigate the relationships among inventive activity and potential inventors, regional technology levels, and regional productivity outcomes. Our results show almost no significant direct relationship between invention and productivity, except through technology. Clearly, the simplification of the "invention in/productivity out" model does not hold, which supports other work that questions the use of patents and patenting related measures as meaningful innovation inputs to processes that generate regional productivity and productivity gains. We also find that the most effective measure of regional inventive capacity, in terms of its effect on technology, productivity, and productivity growth is the share of the workforce engaged in creative activities.

Keywords: Innovation, Productivity, Regional Technology, Patents, Human Capital, Creative Class

JEL: C31, O1, O31, O47, R11, Z10

1. Introduction

The claim that knowledge creation and knowledge spillovers are the twin engines of economic growth has become something of a truism within the economics profession (Romer, 1986, 1987, 1990). The process by which knowledge creation leads to prosperity has been conceived as occurring in two stages. First, an invention or innovation is generated, and then it is developed and commercialized to create benefits for the individual or firm owning the idea. The underlying logic can be succinctly summarized as "innovation in, productivity gains out." Lucas (1988) explicitly identified the role of human capital—the stock of competences, information, skills and experiences embodied in individuals—in the generation of knowledge creation and technological change. Jones and Romer (2010) recent review of our current understanding of the sources of economic growth highlight the crucial role of individuals generating and sharing ideas (that is, knowledge).

Building on Romer's work, and that of Jane Jacobs (1969, 1984), Lucas drew attention to the positive externality effects of human capital clustering, and the role of cities as centers for the integration of human capital and incubators of invention. As Glaeser (1996, 2000) has pointed out, the perspective that growth hinges on the flow and exchange of ideas naturally leads to recognition of the social and economic role of urban centers in furthering intellectual cross-fertilization. A wide range of empirical studies have documented the role of human capital in regional growth. Barro (1991), Mankiw, Romer and Weil (1992), Rauch (1993), Simon and Nardinelli (1996) and Simon (1998) all substantiate the relation between human capital and growth at a national level. Ullman's (1958) work on regional development noted the role of human capital (before the term was in vogue). Andersson (1985a, b) stressed the importance of knowledge, culture, communications, and creativity in stimulating creativity in cities and regions. Feldman and Florida (1994), Bhatta and Lobo (2000), Glaeser (2000), Florida (2000b), among many other studies, document the association between human capital and regional (sun-national) economic development.

Reminiscent of the difficulties in detecting knowledge-spillovers, human capital is easier to theorize about than to actually measure. The standard approach, dating from Becker's work (Becker, 1964) for measuring human capital is educational attainment, usually the share of a population with a bachelor's degree and above. Recent studies, however, show that this measure does not fully capture an individual's accumulated experience, nor their creativity, innovativeness, and entrepreneurial capabilities. One line of research (Florida, 2002) suggests an alternative measure for human capital, based on the occupation, specifically a set of occupations that make up the "creative class" including science, engineering, arts, culture, entertainment, and the knowledge-based professions of management, finance, law, healthcare and education. Andersson (1985a, b) suggested a similar occupational based measure in the 1980s, to better account for regional human capital levels. Comparative studies show that the creative class measure outperforms conventional human capital measures in accounting for regional development in the U.S. (Florida, Mellander, and Stolarick, 2008), Sweden (Mellander and Florida, 2006), the Netherlands (Marlets and Van Woerken, 2004), and others.

Another measure of human capital is implicit in the work centered on elucidating the determinant of metropolitan patenting. Despite many important caveats, patents have become a widely used metric in studies of the "knowledge economy" and technological change (e.g., Acs and Audretsch, 1989; Griliches, 1990; Jaffe et al., 1993; Jaffe and Trajtenberg, 2002). Patent analysis has therefore become a well-established framework for investigating locational and spatial aspects of technological advance with much effort having been devoted elucidating the determinants of urban patenting productivity (see, for example, Acs, Anselin and Varga, 2002; Bettencourt, Lobo and Strumsky, 2007; Hunt, Carlino and Chatterjee, 2007; Knudsen et al., 2008; Lobo and Strumsky, 2008). Patents are generated by inventors: to study locationally-specific invention (proxied by patents) is to study the agglomeration of one type of skilled and creative individuals, namely inventors. As argued by Hall, Jaffe, and Trajtenberg (2001), patents have numerous advantages as data for the study of innovation and technological change: (1) patents contain highly detailed information on the innovation itself, but also about the inventor, the originating technological area(s) and industry, etc; (2) there is both a very large "stock" and "flow" of patents, so a wealth of data is available for research; and (3) patent count data reaches back at least 100 years, making available a very long time series of data. Of course, simple patent count data also have serious limitations. First, not all inventions or innovative ideas are patented or patentable. Second, patented inventions vary enormously in their technological and economic importance and simple patent counts are seriously insufficient in capturing this underlying heterogeneity. Assessing the economic quality of patented inventions would require the means to track their commercialization or licensing success, data for which is neither comprehensibly nor reliably available. One way of measuring the intellectual quality of patents is through patent citations, that is, the citations made by a patent to other patents. The idea behind using patent citation counts as a measure of quality is that a patent cited by many later patents is likely to contain useful ideas or technologies upon which later inventors are building (see, e.g., (Trajtenberg, Hall, Jaffe and Trajtenberg, 2001, 2005). All in all, we should heed Trajtenberg's caution and consider patent counts as an indicator of the input side of the innovative process, as in R&D expenditures.

Educated, creative or inventive individuals: who are more likely to engender the sort of innovation that fuels economic prosperity? We recognize, of course, the difficulties in empirically differentiating their effects: the inventive and creative are most likely to be highly educated, many employed in creative occupations are likely to be working in industries in which patenting is important (and encouraged), but patenting is irrelevant to many economically significant creative activities. To try and disentangle these issues we present a stage-based general model of regional productivity. In the first stage, we examine how various alternatives for measuring regional innovative individuals affect regional technological outcomes. In the second stage, we look at how both innovative individuals and regional technology impact productivity levels and growth. This stage-based model structure enables us to isolate the direct and indirect effects of these factors in the overall system of regional productivity development. We use structural equations and path analysis models to examine the independent effects of patent inventors, human capital, the creative class, technology diversity and concentration, and other factors identified in the literature on both regional productivity levels (regional GDP per capita) and productivity growth. We examine these issues via multiple cross sectional analyses of 361 metropolitan regions in the United States, and explicitly control for the effects of regional size.

The theory underpinning the present study is a progression from the recent literature examining the geographic determinants of innovation. This literature is, in part, based upon the "knowledge production function" approach introduced by Griliches (1979). The typical economic production function examines the effects of particular inputs on the production of outputs. In this vein, the knowledge production function considers the effects of such typical inputs as R&D expenditures and human capital on such outputs as economic growth, productivity, or innovation. Griliches (1979, 92-93) regards "…total output or total factor productivity as a function of past R&D investments (and other variables). Here *all* productivity growth (to the extent that it is measured correctly) is related to *all* expenditures on R&D and an attempt is made to estimate statistically the part of productivity growth that can be attributed to R&D (and sometimes, also, to its components)".

Our modeling approach is designed to address a significant weakness of previous studies of the effects of patenting and human capital on regional productivity. Most of these studies use a single equation regression framework to identify the direct effects of invention and other factors on regional development. The findings of these studies, not surprisingly, indicate that human capital and regional patenting outperform other variables. But that does not mean that other variables do not matter. First of all, alternative, perhaps more general, measures of regional inventive capacity are available. As has been discussed, both human capital and patents as measures have limitations. It may well be that some variables that have not performed well in other studies exert influence by operating through regional technology and thus indirectly effect regional productivity, or that certain variables operate through different channels. By using a system of equations our model structure allows us to parse the direct and indirect effects of key variables on each other as well as on regional development. The staged model more accurately reflects the underlying situation. Furthermore, our model is based on a strong *a priori* theory of the relationships between and among key variables as they shape regional productivity.

The discussion is organized as follows. The next section derives a measure for metropolitan total factor productivity (TFP) starting from a Cobb-Douglass production function for urban economies. The data and variables used in the statistical modeling are described in the third section while section four presents the OLS and Structural Equation Model (SEM) regression results which constitute the core of our findings. Section five concludes. Anticipating our main result we find that once industry structure is controlled for, measures of human capital do not have a discernible effect on metropolitan productivity; however, the distribution of human capital does affect industry structure (composition) which does significantly affect productivity.

2. Metropolitan Total Factor Productivity

We begin with a variation of the "growth accounting exercise" (Solow, 1956, 1957; Abel, Dey and Gabe, 2010). We treat the metropolitan areas of the United States as open economies among which capital and labor can move freely. We assume further that the generation of metropolitan output can be modeled by a Cobb-Douglass production function so that output (*Y*) is given by:

$$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha} L_{i,t}^{1-\alpha}, \tag{1}$$

where *A* is Hicks-neutral technology (often referred to as "total factor productivity" or "TFP"), *K* is physical capital, *L* is the amount of labor available in a metropolitan area, α is an economy-wide production parameter, and *i* and *t* index place and time, respectively. The choice of a Cobb-Douglas production function, with the concomitant assumption of constant returns to scale to the factors of production, is justified by the fact that the ratio of metropolitan labor income to metropolitan total income ($1 - \alpha$) has remained about 0.7 for all metropolitan areas over the past forty years for which data is available.

Data on metropolitan stocks of physical capital are not readily available; we address this data scarcity by first deriving the rental price of capital and then using the derived capital-demand function to substitute the factor price for the factor quantity. Solving equation (1) for the marginal product of capital in a metropolitan area, and equating it to the rental price of capital, gives:

$$\frac{\partial Y}{\partial K} = r_{i,t} = \alpha A_{i,t} K_{i,t}^{\alpha-1} L_{i,t}^{1-\alpha}. \tag{2}$$

Substituting (1) into (2) yields the following expression for *r*:

$$r_{i,t} = \alpha Y_{i,t} K_{i,t}^{-1}, \tag{3}$$

from which the following capital-demand function can be obtained:

$$K_{i,t} = \frac{\alpha}{r_{i,t}} Y_{i,t}. \tag{4}$$

Equation (4) can then be used to substitute for the amount of physical capital in the production function (1):

$$Y_{i,t} = A_{i,t} \left[\frac{\alpha}{r_{i,t}} Y_{i,t} \right]^{\alpha} L_{i,t}^{1-\alpha}. \tag{5}$$

Solving equation (5) for *Y* results in equation (6), a production function in which metropolitan output is the result of location-specific technology and labor, multiplied by a constant term (ϕ) consisting of capital's share of output and the rental price of capital:

$$Y_{i,t}^{1-\alpha} = \left(\frac{\alpha}{r_{i,t}} \right)^{\alpha} A_{i,t} L_{i,t}^{1-\alpha}. \tag{6}$$

Assuming free mobility of capital allows us to in turn assume, not to heroically, that the rental price of capital is everywhere the same or nearly the same; the $\left(\alpha / r_{i,t}\right)$ can thus be treated as a constant. An expression for output per worker can be obtained by dividing both sides of equation (6) by total metropolitan employment:

$$\left(\frac{Y_{i,t}}{L_{i,t}}\right)^{1-\alpha} = y_{i,t}^{1-\alpha} = \phi_t A_{i,t}. \tag{7}$$

$$\Rightarrow y_{i,t} = \phi_t A_{i,t}^{\frac{1}{1-\alpha}}. \tag{8}$$

From equation (8) we can therefore conclude that metropolitan TFP is approximated by output per worker.

We hypothesize that metropolitan TFP is a simple multiplicative function of location-specific socio-economic and demographic characteristics:

$$A_{i,t} = \prod_{j=1}^{J} X_{i,j,t}^{\beta_j}, \tag{9}$$

where *j* indexes the variables representing the determinants of metropolitan productivity. We are particularly interested in elucidating the effects of different types of human capital on metropolitan output per worker.

3. Metropolitan Variables

Our spatial units of analysis are the 361 Metropolitan Statistical Areas (MSAs) of the continental United States. MSAs, which are defined by the U.S. Office of Management and Budget, are standardized county-based areas having at least one urbanized area (with 50,000 or more population) plus adjacent territory with a high degree of social and economic integration with the core as measured by commuting ties. Metropolitan areas are in effect unified labor markets.

3.1 Dependent variable

For measuring metropolitan productivity (i.e., output per worker), we avail ourselves of the data on *Gross Metropolitan Product* (GMP) provided by the Commerce Department's Bureau of

Economic analysis (BEA). GMP is the metropolitan counterpart to national Gross Domestic Product (GDP), and it's a comprehensive measure of the value of the goods and services produced within metropolitan areas (Panek, Baumgardner and McCormick, 2007). Real GMP is reported using chained-weighted 2005 dollars. Dividing GMP by metropolitan total employment (defined by the BEA as encompassing the number of full and part-time jobs) we get a measure of metropolitan output per work: *Gross Metropolitan product per worker* (*GMPpw*). We utilize two temporal variants of *GMPpw* as dependent variable: a level measure, averaged over the 2007-2009 period, and a change measure between the 2001-2003 and 2007-2009 periods. (Table 1 illustrates the descriptive statistics for all variables.)

3.2 Independent variables

Our analytical purpose is to elucidate whether three distinct ways of measuring the presence in metropolitan areas of skilled individuals—through the proportion of the work force who are engaged in invention, have a college education, or are engaged in creative employment—are statistically distinguishable with regards to their effects on the productivity of urban areas. We first describe the three principal independent variables.

Inventors per worker. We use data on patents granted by the United States Patent and Trademark Office (USPTO). Every granted patent lists the inventors' names and home towns; patents do not, however, provide consistent listings of inventor names or unique identifiers for the authors, so matching procedures were used to uniquely identify inventors across time and locations (the matching procedures are discussed in Marx, Strumsky and Fleming (2009)). By identifying individual inventors and their place of residence at the time the application for the patent was filed, each patent and inventor is assigned to a metropolitan area. (We restrict our analysis to patents whose authors are U.S. residents.) For purposes of calculating metropolitan patent counts, a patent with multiple authors is allocated to of each of the distinct locations in which the authors reside (if several authors reside in the same MSA that location gets its patent count increased by just one). We follow the by now standard convention of counting patents on the year the patent was successfully applied for so as to measure inventive activity as close as possible to the moment of invention. Metropolitan inventors per worker is defined as the total number of metropolitan-based inventors, in a given application year, divided by the MSA's total employment in that given year. The variable *inventors* is measured per 10,000 workers.

Educational attainment measures the presence of skilled individuals as the percentage of metropolitan adult (25 and older) workers with a Bachelors degree or higher—thereby implicitly equating possessing high skill levels with a college education. The data is for 2001 and is from the U.S. Census.

Creative employment. Creative employment is measured as the share of the labor force whose work tasks include complex problem solving. Included are occupations such as computer and math; architecture and engineering; life, physical, and social science; education, training, and library positions; arts and design work; and entertainment, sports, and media occupations—as well as other "creative professionals," akin to classical knowledge workers, including management occupations, business and financial operations, legal positions, healthcare practitioners, technical occupations, and high-end sales and sales management. The definition is based on Florida (2002) and due to data restrictions the variable is for the year 2005, that is, for a later time period that the other explanatory variables. However, regional occupational structure can be considered a relatively slow variable, in other words, we do not expect it to change rapidly.[1]

[1] A year to year correlation analysis for the same creative employment variable for the year 2006 to 2009 illustrates the slow change over time, with correlations of approximately 0.8-0.95 (Stolarick and Currid, 2011).

The econometric estimations also include other variables meant to control for salient socio-economic features of metropolitan areas which can influence the productivity-enhancing effects of human capital. These additional control variables are described next, starting with measures for the quality and productivity of inventive (i.e., patenting) activity.

Patent citations. We hypothesized that the contribution to aggregate productivity made by a metropolitan area's inventive work force is modulated by the quality of its inventive efforts. Assessing the economic quality of patented inventions would require the means to track their commercialization or licensing success, data for which is neither comprehensibly nor reliably available. One way of measuring the intellectual quality of granted patents is through patent citations, that is, the citations made to a patent by other patents. (The USPTO requires that authors of patent applications disclose any relevant "prior art", that is, any intellectual material, such as previous patented inventions patents and scientific literature, that is pertinent to the determination of novelty patentability. References to previous patents are recorded as patent citations.) The idea behind using patent citation counts as a measure of quality is that a patent cited by subsequent patents is likely to contain useful ideas or technologies upon which later inventors are building.[2] Citations made to a granted patent by subsequent patents are counted up to the end of the period covered by our database (December 31st, 2010). The measure *patent citations* is constructed by counting the citations received, from the application year onwards, by granted patents assigned to a metropolitan area, and the dividing that count by the number of patents generating the citations. (It takes time for a patent to accumulate a large number of citations from later patents, but most citations are accumulated within eight years of a patent being granted.)

[2] Studies have established a strong positive relationship between highly cited patents and technological importance, stock market valuations, and firm profitability (Albert, Avery and McAllister, 1991; Hall, Jaffe and Trajtenberg, 2001, 2005; Trajtenberg, 1990; Trajtenberg, Henderson and Jaffe, 1997).

Patents per inventor. This variable, defined as the total number of patents generated by metropolitan-based inventors divided by the number of inventors, is meant to capture how productive a metropolitan inventive community is. A high value for this productivity measure can be an indication of the quality of the inventors residing in an urban area.

We also control for agglomeration economies, market size and industry structure by means of these variables.

Population. Among the many possible determinants of location-specific productivity, agglomeration economies—a set of phenomena ultimately dependent on the size and density of urban populations—have been among the most extensively studied (see, for example, Shefer, 1973; Sveikauskas, 1975; Segal, 1976; Carlino, 1979; Moomaw, 1981, 1988; Rosenthal and Strange, 2004; Bettencourt, Lobo and Strumsky, 2007; Hunt, Carlino and Chatterjee, 2007; Puga, 2010). Population size also serves to measure the size of an urban area´s market. We therefore include a control for the population size of a metropolitan area.

Population density. The opportunities for both coordinated and serendipitous information flows, and for knowledge spillovers to occur, are considered greater in denser areas (Carlino, Chatterjee and Hunt, 2007; Knudsen et al., 2008). Our estimations included two measurements for metropolitan population density: the one, which divides total population by the total area represented by an MSA´s constituent counties, and a weighted-measure, in which the contribution of a county´s area is weighted by its share of total population.

Establishments per Worker. We needed a measure of a local area's market structure so as to test whether knowledge spillovers, which foster patenting, are greater if an MSA is more competitive. The total number of establishments (i.e., work places) per worker in an MSA is used as a measure of market structure, *i.e.*, an MSA is taken as locally competitive if it has more firms per worker.

Large Firms Share. Since large firms tend to spend proportionately more on private R&D than do smaller firms, the percentage of an MSA's firms with 1,000 or more employees is included to capture the effects of large firms on patenting activity.

High Tech Concentration. We include a technology variable to account for the effects of technology on regional productivity. This technology variable is based on the "Tech-Pole Index" published by the Milken Institute (Devol et al., 2001). This index scores metropolitan areas based on: (1) high-tech industrial output as a percentage of total U.S. high-tech industrial output; and (2) the percentage of the region's own total economic output that comes from high-tech industries compared to the nationwide percentage. The numbers are updated using the U.S. Census County Business Patterns and are from 2006.

Technology Diversity. The Patent Office classifies all patents into 481 technological classes, for example, class 437 (Semiconductor Device Manufacturing: Process) and 977 (Nanotechnology).[3] To control for the technological heterogeneity and diversity within each metropolitan inventive community, we calculated a Technology Herfindahl index for an area's patent applications using the U.S. Patent Office's technology classes. In the analysis we employ the inverse of the Hirfindahl index, which implies that higher values mean more diversity.

(Table 1 about here.)

[3] For a listing of the USPTO technology classes go to www.uspto.gov/go/classification/selectnumwithtitle.htm.

Table 1: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variables:					
Av GRP 07-09 per worker	361	39514	125562	61812	12472
GRP per worker change 01-03 to 07-09 (%)	361	-0.2188	0.9489	0.049538	0.0893
Tech Variables					
High Tech Concentration	334	0.0002	8.5273	0.2447	0.848
Tech Diversity	360	0.0089	1.000	0.0931	0.116
Explanatory Variables:*					
Av Patent Applications per Worker	361	0.186	116.515	5.413	9.614
Av Patent Citations per Worker	361	1.261	9.916	3.604	1.134
Patents per Inventor	360	.2985	1.1833	.5091	.1207
Human Capital (%)	361	0.1033	0.5445	0.2104	0.0708
Creative Employment Share (%)	341	0.11	0.44	0.2682	0.04845
Control Variables					
Av Population	361	54311	18583811	661260	1521039
Av Population Density	361	6.00	9242	319.5	626.7
Av Weighted Population Density	361	6.00	17330	476.5	1063.9
Employees per Establishment	361	6.28	22.45	15.414	2.755
Large Establishment Share	361	0	0.0059	0.0015	0.0008

* all explanatory variables are expressed as averages for the year 2001-2003, except for creative employment (2005)

Before turning our attention to the regression results, we present and discuss the correlations among the various metropolitan variables in an attempt to tease out the bivariate relations among them. Since we expect to find an increase in productivity as market size increases, we also use partial correlations with a population control to rule out the possibility that the relations are driven purely by urban size. (Results are shown in Table 2). Correlations were calculated for both Gross Metropolitan Product per worker (*GMPpw*) and the percent change in output per worker from the 2001-2003 to the 2007-2009 windows (denoted by $\%\Delta GMPpw$).

(Table 2 about here.)

Table 2: Bivariate and Partial Correlations

	Bivariate Correlations		Partial Correlations	
	GMP per worker 2007-2009	GMP per worker Change	GMP per worker 2007-2009	GMP per Worker Change
Productivity:				
GMP 2007-2009	-	.301***	-	.367***
GMP Change	.301***	-	.367***	-
Market Size:				
Population	.602***	.024	-	-
Technology				
High Tech Concentration	.641***	.198	.248***	.014
Tech Diversity	.414***	.030	-.005	-.014
Inventors:				
Patent Applications per Worker	.320***	.214***	.137**	.221***
Patent Citations per Worker	.265***	.102*	.097*	.108**
Patents per Inventor	-.276***	-.072	-.065	-.018
Educated:				
Human Capital	.321***	.137***	.176***	.148***
Creatives:				
Creative Employment	.396***	.224***	.161***	.240***
Other:				
Population Density	.435***	-.037	.028	-.065
Weighted Population Density	.498***	-.032	.063	-.076
Large Establishment Share	.135**	.030	-.013	.015
Employees per Establishment	.231***	.043	.047	.006

***indicate significance at the 0.01 level, ** at the 0.05 level, and * at the 0.1 level.
All variables are logged except change in GMP.

From Table 2 we see that, as expected, *GMPpw* tends to be higher in regions with higher levels of population (0.602). However, we find no significant relation between %ΔGMPpw change and population, in other words, productivity levels have not increased faster in bigger regions. We find a positive and significant relation with high tech concentration and *GMPpw* (0.641), which also stays significant in the partial correlations (0.248), but is insignificant to changes in *GMPpw*. Technology diversity is also significantly related to *GMPpw*, and higher levels of diversity implies higher levels of *GMPpw* (0.414). The relation becomes insignificant in the partial correlations, and is not significantly related to changes in *GMPpw*.

The correlation between patenting and *GMPpw* is positive and significant, both in terms of inventors per worker (0.320) and patent citations (0.265). There is also a positive, but slightly weaker significance, between inventors and productivity change (0.214 vs. 0.102). These relations also hold when we control for population size in the partial correlations, but become somewhat weaker. However, the relation between patents per inventor and *GMPpw* is negative and significant (-0.276), This relation becomes insignificant once regional size is controlled for. Neither is there a significant relation between patents per inventor and *%∆GMPpw*.

We find a similar pattern for *educational attainment* as we do for *inventors*. Metropolitan areas with higher shares of human capital also have higher levels of productivity (0.321), and have seen a larger increase in productivity over the last decade (0.137). These relations also hold, once regional size in terms of population is controlled for in partial correlations. Creative employees generates a similar result, with positive and significant relations to *GMPpw* (0.396) and change in *GMPpw* (0.224), and is somewhat more strongly related to *GMPpw* and *%∆GMPpw* than both inventors and educated. The relation between creative employees and productivity also stays significant in the partial correlations.

We find that the variables measuring population density, industry structure, share of larger firms and employees per establishment, are positively correlated with metropolitan productivity. However, they are not significantly correlated with the percent change in output per worker. Furthermore, the positive relations between these variables and productivity becomes insignificant once population size is controlled for. In other words, productivity increases due to density and industry establishment size effects may well be a proxy for bigger market places. Generally speaking, we find a positive and significant relation between inventors, educated and creatives, and regional productivity, both in absolute terms and in terms of changes over time, but also significant market size effects.

4. Regression Results

We now turn to the multivariate regression analysis so as to study the relationship between metropolitan productivity (levels and percent change), and the educated, the creatives and the inventive. We ran estimations using the inventors, educated, and creatives measures, individually and also with all three in combination, since they are overlapping, but not identical proxies for regional talent levels.[4] We subsequently used structural equation modeling (SEM) to examine alternative structural relationships between inventors, educated and creatives in relation to metropolitan productivity while taking into account industry (i.e., economy) structures into account.

Utilizing data on Gross Metropolitan Product does impose a significant constraint on the analysis' temporal coverage as the data is only reported for the 2001-2009 period. Due to data constraints, we will estimate this as cross-section, and not a panel over time. To decrease endogeneity problems, we will use lagged explanatory variables (averages for 2001 to 2003) to explain our dependent variable Gross Metropolitan Product per worker (average for 2007-2009) and change in Gross Metropolitan Product per worker (change between the per worker average in 2001-2003 and the average in 2007-2009). While our models will assume a one-way causality, we admit that in the long run, one can expect feedback loops in such a structure, with both selection and sorting issues. It is important to note that by using 2009 data we capture regional productivity in a post-crisis U.S.

Structural Equation Modeling (SEM) can be thought of as an extension of regression analysis, expressing the interrelationship between variables through a set of linear relationships, based upon their variances and covariances (for further technical description see Jöreskog, 1973:

[4] The correlation between the three are; .576 (inventors and educated), .447 (inventors and creatives), and .484 (educated and creatives).

Kline, 2010). The parameters of the equations are estimated by the maximum likelihood method. We graph our assumed relations in Figure 1 below. Structural equation modeling is commonly used when one or several included variables are latent. It is not a necessary condition however to include latent variables in order to use structural equation modeling. In our analysis, all included variables are observable. The causality in the graphic figure is completely based on theoretical assumptions, since SEM expresses direct and indirect correlations, and not actual causalities. In other words, the parameters we estimate provide information about the relation among the set of variables. The relative importance of the regression coefficients is expressed by standardized path coefficients, while the unstandardized path coefficients are expressed as elasticities (when only logged variables are employed). We do not assume any causality between inventors, educated and creatives but will treat them as correlations.

From the relationships depicted in Figure 1, we estimated the following versions of equation (9), estimating both indirect effects (equation 10 and 11 below) as well as direct effects (equation 12 and 13 below) from the inventive, educated, and creative, together with market size and industry structures, in order to explain GMP per worker and change in GMP per worker:

(Figure 1 about here.)

The first two sequences determine industry structures in terms of technology diversity and concentration;

$$\begin{aligned}\ln TechDiversity &= \beta_{11} \ln Inventors + \beta_{12} \ln Educated \\ &+ \beta_{13} \ln Creatives + \beta_{14} \ln Population + e_1,\end{aligned} \tag{10}$$

$$\begin{aligned}\ln TechConcentration &= \beta_{21} \ln Inventors + \beta_{23} \ln Educated \\ &+ \beta_{24} \ln Creatives + \beta_{24} \ln Population + e_2.\end{aligned} \tag{11}$$

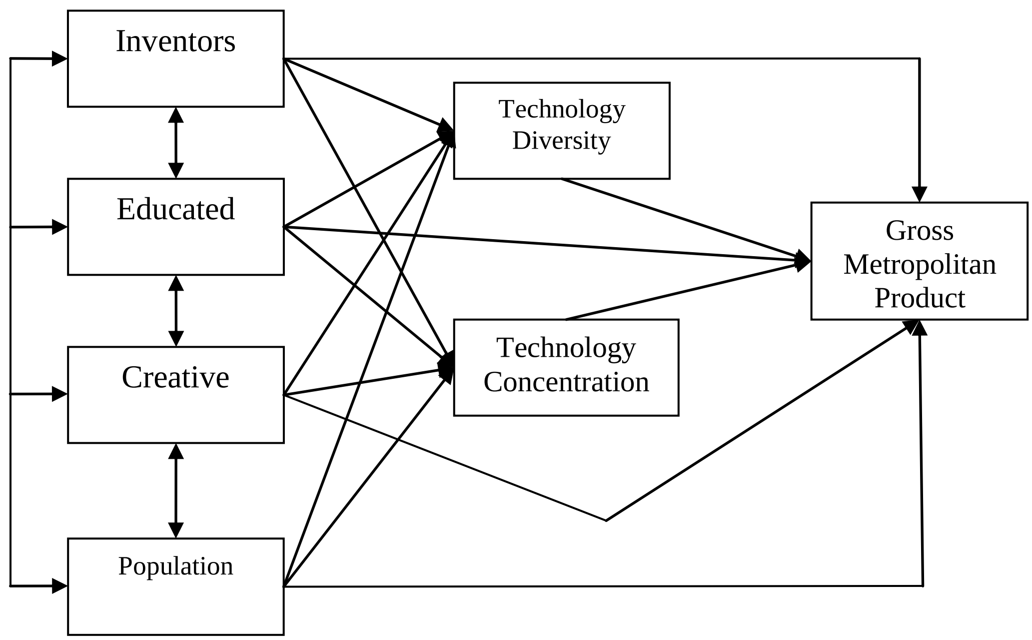

Figure 1: Two Stage Model of Innovation, Technology, Productivity

In the third and last sequence, explanatory and dependent variables from equation 10 and 11 will all be used as explanatory variables in order to explain (1) GMP per worker, and (2) change in GMP per worker, and thereby take into account both indirect and direct effects;

$$\ln GMPperWorker = \beta_{31} \ln Inventors + \beta_{34} \ln Educated + \beta_{35} \ln Creatives + \beta_{34} \ln Population + \beta_{35} \ln TechDiversity + \beta_{36} \ln TechConcentration + e_3 \tag{12}$$

$$\%DGMPperWorker = \beta_{31} \ln Inventors + \beta_{34} \ln Educated + \beta_{35} \ln Creatives + \beta_{34} \ln Population + \beta_{35} \ln TechDiversity + \beta_{36} \ln TechConcentration + e_3 \tag{13}$$

Before turning to the sequential regression modeling, we will employ a traditional OLS regression model to later be able to compare results.

4.1. <u>OLS Results</u>

We begin with the findings from the OLS regressions, which are based on equations (10) and (11), that is, without indirect effects taken into account. The first set of regression results

(Table 3) use *GMP per worker* as dependent variable with columns 1 to 3 showing the results from utilizing each of the three measures one at a time, while column 4 shows the results from an estimation done using all three variables.

(Table 3 about here.)

Table 3: OLS regressions for GMP per Capita

	1. Inventors	**2. Educated**	**3. Creatives**	**4. Combined**
Inventors	.016*	-	-	.012
	(.010)			(.010)
Educated	-	.035	-	.006
		(.034)		(.036)
Creatives	-	-	.066	.055
			(.052)	(.053)
Tech Concentration	.029***	.029***	.026***	.023***
	(.007)	(.008)	(.008)	(.014)
Tech Diversity	-.031**	-0.025*	-.023*	-.032**
	(.014)	(.013)	(.012)	(.014)
Population	.080***	.079***	.077***	.084***
	(.014)	(.014)	(.013)	(.015)
R2	.467	.464	.460	.463
R2 Adj.	.460	.457	.453	.452
N	332	332	317	317

Table 3 illustrates a clear relationship between industry structures and GMP per capita. Regions with high technology concentration and low technology diversity have higher levels of GMP per capita. Market size, in terms of population, is also consistently strong, positive and significant. Turning to the three different talent variables, it is only inventors that seem to have a significant relation with GMP per capita, and then only at the 10 percent level. When combined with educated and creative it looses its weak significance and become insignificant. The OLS results would suggest that talent, in terms of inventors, educated, and creatives have little to do with regional productivity, but that this is mainly a result of industry structure.

Next, we run the same set of regressions, but now employ change in GMP per worker as dependent variable.

(Table 4 about here.)

Table 4: OLS regressions for Change in GMP per Capita

	1. Inventors	**2. Educated**	**3. Creatives**	**4. Combined**
Inventors	.008	-	-	-.003
	(.005)			(.016)
Educated	-	-.037*	-	-.041
		(.019)		(.021)
Creatives	-	-	.052*	.065**
			(.030)	(.030)
Tech Concentration	.016***	.023***	.015***	.019***
	(.004)	(.005)	(.004)	(.005)
Tech Diversity	-.017**	-0.007	-.011	-.006
	(.008)	(.013)	(.007)	(.007)
Population	-.013	-.023***	-.016***	-.023***
	(.008)	(.008)	(.007)	(.008)
R2	.077	.081	.079	.092
R2 Adj	.065	.070	.067	.074
N	332	332	317	317

Also in this case, we find a strong and positive relation between technology concentration and change in GMP per capita. Technology diversity is in principal insignificant. Only in regression 1, in combination with inventors, is it significant and negative. Population is negative and significant in regression 2-4, indicating that bigger market places have experienced less GMP per capita growth over the last decade. Both inventors and educated are insignificant in all four regressions. However, creatives are weakly positive and significant in regression 3, and even stronger when combined with inventors and educated in regression 4. This indicates that higher levels of creative workers affect growth in GMP per capita positively. Still, industry structure determines more of productivity growth than different forms of talent.

Overall, the results from Tables 3 and 4 suggest that industry structures play a far more important role than the regional distribution of talent labor. To further explore these relations, we suggest that talent labor may play a more indirect effect, and that inventors, educated and creatives may each do so differently. We therefore leave the more simplified OLS regressions and move to a structural framework, where talent labor is allowed to play an indirect role for productivity as determinants for industry structures.

4.2. Structural Equation Modeling

We begin with the findings from the GMP per Worker regressions. Table 5 illustrates the results for all three regressions, taking both unstandardized and standardized coefficients into account. Given the close relation between patent applications and patent citations, we will only employ patent applications as a proxy for inventors in the multivariate regression analysis. (We also re-ran all regressions including patent citations per worker alongside patent applications. The variable turned out insignificant in all versions of the model.) Further, we will employ the "Combined" model as our baseline model, in other words, where we include all three labor variables (inventors, educated, and creatives). However, we will also run one SEM where they are employed one at a time, to be able to compare the results, and avoid that the results are driven by multicollinearity problems.

The first regression in the "Combined model" for Tech Diversity the strongest explanatory variable is population, with a standardized coefficient of .601. This is followed by inventors (.382) and educated (.157). All three variables significantly add to an increased technology diversity, and together they explain approximately 60 percent of the variation. However, creatives is insignificant in relation to tech diversity.

(Table 5 about here.)

Table 5: Regression Results for GMP per Worker SEMs for Inventors, Educated, Creatives and Combined

INVENTORS	(1) Tech Diversity	(2) Tech Concentration	(3) GMP per Worker
Inventors	0.360/.422*** (0.028)	0.535/.282*** (0.055)	0.019/.110* (0.010)
Educated	-	-	-
Creatives	-	-	-
Population	0.476/.556*** (0.029)	1.393/.730*** (0.055)	0.069/.396*** (0.014)
Tech Concentration	NA	NA	0.033/.359*** (0.008)
Tech Diversity	NA	NA	-0.037/-.184*** (0.014)
N	361	361	361
Sq. Multiple Corr.	.645	.750	.421
EDUCATED	(1) Tech Diversity	(2) Tech Concentration	(3) GMP per Worker
Inventors	-	-	-
Educated	0.939/.320*** (0.104)	2.403/.370 *** (0.167)	0.051/.085 (0.034)
Creatives	-	-	-
Population	0.524/.611*** (0.029)	1.362/.717*** (0.049)	0.068/.392*** (0.015)
Tech Concentration	NA	NA	0.033/.359*** (0.008)
Tech Diversity	NA	NA	-0.031/-.154** (0.013)
N	361	361	361
Sq. Multiple Corr.	.582	.795	.424
CREATIVES	(1) Tech Diversity	(2) Tech Concentration	(3) GMP per Worker
Inventors	-	-	-
Educated	-	-	-
Creatives	0.929/.310*** (0.208)	3.351/.191*** (0.339)	0.067/.068 (0.055)
Population	0.520/.607*** (0.036)	1.289/.677*** (0.059)	0.061/.353*** (0.014)
Tech Concentration	NA	NA	0.033/.361*** (0.008)
Tech Diversity	NA	NA	-0.024/-.119**

			(0.012)
N	361	361	361
Sq. Multiple Corr.	.515	.754	.417
COMBINED	(1) Tech Diversity	(2) Tech Concentration	(3) GMP per Worker
Inventors	0.298/.382***	0.181/.109***	0.014/.087
	(0.033)	(0.056)	(0.010)
Educated	0.420/.157***	1.640/.287 ***	0.039/.068
	(0.117)	(0.196)	(0.034)
Creatives	-0.092/-.021	1.690/.178***	0.038/.041
	(0.183)	(0.303)	(0.051)
Population	0.471/.601***	1.228/.734***	0.075/.453***
	(0.026)	(0.044)	(0.015)
Tech Concentration	NA	NA	0.027/.275***
			(0.009)
Tech Diversity	NA	NA	-0.040/-.190**
			(0.014)
N	361	361	361
Sq. Multiple Corr.	.591	.767	.369

unstandardized/standardized coefficient, standard errors within brackets.
*** indicates significance at the 0.01 level, ** at the 0.05 level, and * at the 0.1 level

The regression for tech concentration shows a similar pattern. Once more, population is the strongest variable, with a standardized coefficient of 0.734. But still, educated (0.287), creatives (0.178), and inventors (.109) add to the explanatory power, all significant at the 1 percent level. The regression generates a squared multiple correlation of approximately 0.767, suggesting that close to 80 percent of the variation is explained by the included explanatory variables. It is worth noting that educated is relatively stronger than inventors, in the tech concentration regression, while the opposite is true in the tech diversity regression. Creatives are, in other words, only significantly related to tech concentration, and not tech diversity.

In the final GMP per worker regression, population still plays a strong and significant role, as expected. The standardized coefficient is 0.453, which is the relatively strongest. Tech concentration is also strong and significant, with a standardized coefficient of 0.275. This indicates that bigger markets with higher levels of high tech concentration are more productive in general. Somewhat interestingly, we find a negative and significant relation from tech diversity and productivity, indicating that more diversity generates lower levels of productivity. This would imply that scale alone is a productivity enhancer, while diversity is not, in this context. The regression generates a squared multiple correlation of 0.369. Neither inventors, educated nor creatives have a significant relation with productivity levels, once technology structures and market size is taken into account. However, as the model structure suggests, they still play a crucial indirect role by its affect on the distribution of technology structures.

When we compare the combined model with the regressions where our three different labor variables are employed one at a time, we note that inventors tend to provide the strongest explanatory power for technology diversity of the three, with a generated squared multiple correlation of 0.645 compared to 0.582 for educated and 0.515 for creatives. On the other hand, educated provides a stronger explanatory power in relation to technology concentration (0.795), compared to creatives (0.754) and inventors (0.754). In terms of direct effects on GMP per worker, only inventors remain significant (and then only at the 10 percent level), while neither educated nor creatives remain significant, when employed one at a time.

To parse out the indirect, direct and total effects from inventors, educated and creatives, we isolate their results from the regressions. Table 6 illustrates this, both expressed as unstandardized and standardized coefficients in relation to GMP per worker. The top part of the table illustrates the results when inventors, educated, and creatives are employed one at a time, while the bottom part of the table is for our baseline combined model.

(**Table 6 about here.**)

Table 6: Indirect, Direct, and Total Effects on GMP per Worker

	Unstandardized			Standardized		
	Inventors	Educated	Creatives	Inventors	Educated	Creatives
One at a time						
Indirect	.004	.050	.088	.024	.083	.089
Direct	.019	.051	.067	.110	.085	.068
Total	.023	.100	.155	.133	.169	.157
Combined						
Indirect	-0.007	0.028	0.05	-0.043	0.049	0.053
Direct	0.014	0.039	0.038	0.087	0.068	0.041
Total	0.007	0.066	0.088	0.044	0.117	0.094

The unstandardized effects (left side of Table 6) illustrate the elasticities in relation to GMP per worker. For the combined model, a one percent increase in inventors implies a -0.7 percent indirect and a 1.4 percent direct change in GMP per Worker. A 1 percent increase in educated implies a 2.8 percent indirect increase and a 3.9 percent direct increase in GMP per worker, and a 1 percent increase in creative generates a 5 percent indirect and a 3.8 percent direct increase in GMP per worker. If we look at the standardized coefficients (right side of Table 6), which no longer can be interpreted as elasticities, we see that educated and creatives are relatively stronger than the inventors variables, with total effects of 0.117 and 0.094. Educated has stronger direct effects on GMP per Worker (0.068 vs. 0.041), while creatives is relatively stronger in terms of indirect effects (0.053 vs. 0.049).

When inventors, educated, and creatives are employed one at a time, the coefficient values (both unstandardized and standardized) will be slightly increased, given that no other qualified labor control variable is used as control variable. Still, we find that the relative strength of the variables still hold, and are robust in relation to the combined model. Educated are still strongest in relation to GMP per worker (0.169), followed by creatives (0.157) and inventors (0.133). Inventors have the strongest direct effect on GMP per capita (0.110), while creatives have the strongest indirect effect (0.089). Educated are relatively constant with an indirect effect of 0.083 and a direct effect of 0.085.

Next, we turn our attention to the change in GMP per Worker over time regression results. We keep the same initial structures with tech diversity and tech concentration, but substitute GMP per Worker with the Change in GMP per Worker. Once more, we will employ the "Combined" model as our baseline model, where all three labor variables (inventors, educated, and creatives) are included. Again, we will run SEMs where they are employed one at a time, to be able to compare the results, and be able to detect multicollinearity problems. Table 7 illustrates the results for all three regression steps.

(Table 7 about here.)

The first two regressions in the "combined model" (tech diversity and tech concentration) generate similar results as in Table 7 above, as expected. Population is still highly related to tech diversity (.601), followed by inventors (.383) and educated (.156). Creatives is insignificant in relation to tech diversity. Tech concentration is still highly determined by population (.725), followed by educated (.289), creatives (.181), and inventors (.118). The third regression in the structure now has change in GMP per Worker, in other words productivity growth. Interesting enough, population is now negative and significant (-.343), indicating that bigger places have experienced lower levels of productivity increases. Neither is market size the strongest among the explanatory variables any longer. This is instead tech concentration with a standardized coefficient of .460. This indicates that smaller regions but with high tech concentration are regions with the strongest productivity increase. We also find a negative and significant relation

Table 7: Regression Results for Change in GMP per Worker SEMs for Inventors, Educated, Creatives and Combined

INVENTORS	(1) Tech Diversity	(2) Tech Concentration	(3) GMP per Worker Change
Inventors	0.360/.422*** (0.028)	0.588/.292*** (0.055)	0.016/.193*** (0.006)
Educated	-	-	-
Creatives	-	-	-
Population	0.476/.556*** (0.029)	1.390/.724*** (0.056)	-0.022/-.264*** (0.009)
Tech Concentration	NA	NA	0.021/.474*** (0.005)
Tech Diversity	NA	NA	-0.024/-.238*** (0.008)
N	361	361	361
Sq. Multiple Corr.	.645	.751	.124
EDUCATED	(1) Tech Diversity	(2) Tech Concentration	(3) GMP per Worker Change
Inventors	-	-	-
Educated	0.938/.320*** (0.104)	2.471/.378 *** (0.169)	-0.024/.-.082 (0.021)
Creatives	-	-	-
Population	0.523/.611*** (0.030)	1.357/.710*** (0.049)	-0.036/-.430*** (0.009)
Tech Concentration	NA	NA	0.030/.672*** (0.005)
Tech Diversity	NA	NA	-0.010/-.100 (0.008)
N	361	361	361
Sq. Multiple Corr.	.582	.793	.116
CREATIVES	(1) Tech Diversity	(2) Tech Concentration	(3) GMP per Worker Change
Inventors	-	-	-
Educated	-	-	-
Creatives	0.924/.190*** (0.208)	3.440/.316*** (0.341)	0.073/.150** (0.033)
Population	0.520/.607*** (0.036)	1.288/.673*** (0.059)	-.027/-.322*** (0.008)
Tech Concentration	NA	NA	0.019/.439*** (0.005)

	(1)	(2)	(3)
Tech Diversity	NA	NA	-0.012/-.125* (0.007)
N	361	361	361
Sq. Multiple Corr.	.514	.754	.110
COMBINED	(1) Tech Diversity	(2) Tech Concentration	(3) GMP per Worker Change
Inventors	0.298/.383*** (0.033)	0.197/.118*** (0.056)	0.017/.195*** (0.006)
Educated	0.418/.156*** (0.117)	1.658/.289 *** (0.196)	-0.041/-.140** (0.020)
Creatives	-0.090/-.020 (0.183)	1.731/.181*** (0.305)	0.060/.123** (0.030)
Population	0.471/.601*** (0.026)	1.218/.725*** (0.044)	-0.029/-.343*** (0.009)
Tech Concentration	NA	NA	0.024/.460*** (0.005)
Tech Diversity	NA	NA	-0.021/-.190** (0.008)
N	361	361	361
Sq. Multiple Corr.	.591	.766	.175

unstandardized/standardized coefficient, standard errors within brackets.
*** indicates significance at the 0.01 level, ** at the 0.05 level, and * at the 0.1 level

between change in GMP per worker and tech diversity, which implies that tech diversity has a negative impact on change in GMP per worker. Contrary to the results for GMP per worker in absolute terms, both inventors and creatives have a direct, positive and significant relation to change in GMP per worker. In other words, they have both an indirect effect via tech concentration, and direct in relation to change in GMP. Educated, however, has a negative and significant direct effect on change in GMP per worker.

When inventors, educated, and creatives are used one at a time, the results of the first two equations will remain unchanged (given that they in principle are identical with the first two regressions in Table 7 above). When we examine the direct effects from the three on change in GMP per worker, the results are much in line with when they are used combined. Inventors tend to explain relatively more and remains significant at the 1 percent level in the change in GMP per capita regression. Similarly, creatives is significant in the direct relation regression, while educated, which was negative and significant in the combined model, now is insignificant. There is in other words reason to believe that the negative sign for educated in relation to change in GMP is a multicollinearity effect. However, also when the used alone, it is still weaker in relation to change in GMP per worker than inventors and creatives.

To once more capture the different effects from inventors, educated and creatives, we isolate the indirect, direct and total effects for these variables in relation to change in GMP per worker, based on the regression results (Table 8):

(Table 8 about here.)

Table 8: Indirect, Direct, and Total Effects on Change in GMP per Worker

	Unstandardized			Standardized		
	Inventors	Educated	Creatives	Inventors	Educated	Creatives
One at a time						
Indirect	.003	.064	.055	.038	.222	.115
Direct	.016	-.024	.073	.193	-.082	.150
Total	.019	.041	.128	.231	.141	.265
Combined						
Indirect	-0.002	0.03	0.043	-0.018	0.103	0.087
Direct	0.017	-0.041	0.06	0.195	-0.14	0.123
Total	0.015	-0.011	0.103	0.177	-0.037	0.21

Given that the regression is in a log-linear form, the unstandarized coefficients cannot be interpreted as elasticities. For the combined model, we notice a weak indirect effect, but a strong direct effect from inventors on change in GMP per worker. Educated have an opposite relation, where the indirect effect is relatively stronger. For creatives the direct effect is stronger than the indirect effect, and both effects are positive. From the standardized results, we see that creatives, followed by inventors have the strongest total effect on change in GMP per worker. In total, educated has a negative total effect on change in GMP per worker, even though the indirect effect is the strongest among all four variables. Inventors has the strongest direct effect, followed by creatives.

Once more we find robust and consistent results, when we instead employ inventors, educated and creatives one at a time. Due to lack of control variables, the coefficient values become higher, compared to the combined model, but the relative strength still hold between the variables. Creatives is the strongest variable in relation to change in GMP per worker (0.265) followed by inventors (0.231), but clearly inventors have a relatively stronger direct effect (0.193). Educated has the strongest indirect effect (0.222), but is the weakest in terms of indirect effects, and therefore also the weakest in terms of total effects.

Overall, all three – inventors, educated, and creatives – play significant roles in order to explain both GMP per capita and change in GMP per capita, but they do so in different, mainly indirect, ways. Industry structures on the other hand have far stronger direct effects on regional productivity and change in productivity.

5. Discussion

We have investigated the regional relationship between innovation and productivity in a way that more closely approximates the actual situation – inventive people generate ideas that may improve regional technology outcomes which, in turn, helps to generate beneficial productivity outcomes. This modeling is important for a variety of reasons beyond its closer correspondence to actuality. First, it more clearly identifies the relationships among innovative individuals, regional technology, and productivity. Second, it allows for a comparison of various measures of innovators. Third, it emphasizes the importance of individuals to the innovative process which allows for recognition that the impact of innovation on productivity need not necessarily be endogenous. While some innovation accrues locally, some is mobile. Often, an invention can occur in one location while the development and commercialization that created productivity benefits accumulates in a different location. There can be both “buzz” and “pipelines” (Bathelt, Malmberg and Maskell, 2004). The results clearly show that some inventive activity does accrue locally, but the variation in the results and importance of innovation to technology outcomes reveals that the mobility of innovation is also an important consideration – something that is not allowed for when a more standard linear model is used to evaluate these relationships.

Both productivity levels and productivity growth outcomes were considered. Clearly, regional technology, diversity and high-tech concentration, have significant relationships with productivity outcomes. Concentration had a positive relationship while diversity was generally negative and significant to productivity. Economies of scale are more important to regional productivity outcomes than industrial diversity. Regional population is a significant factor and was found to be positively and significantly related to productivity levels and negatively and significantly related to productivity growth.

Inventive individuals were measured three ways: patent applications, education levels, creative employment. While related to each other and overlaps exist, they are not substitutes for each other. They were evaluated both separately and jointly, and their direct impact on regional technology and direct and indirect impact on productivity was considered. In terms of impact on regional productivity levels, little direct affect was found between innovators and productivity. However, innovators were found to positively impact both technology diversity and concentration and through that indirectly impact productivity. Regional human capital and creative class workforce had stronger relationships and greater impact on productivity levels.

Regional productivity growth was also primarily indirectly impacted by innovators through the direct impact on technology. Regional patent inventors and creative workforce had stronger direct relationships and greater impact on productivity growth. Regional human capital had some significant relationships and indications that it may have a negative relationship to regional productivity growth. This could be a result of multicollinearity with the other innovative measures or population size. Overall, creative class had the best and strongest direct and indirect results in predicting both productivity level and productivity growth at the regional level.

A longstanding research tradition assumes that endogenous technological development increases regional productivity. It has been assumed that measures of regional patenting activity or human capital are an adequate way to capture the endogenous creation of new ideas that result in productivity improvements. First, an invention or innovation is generated, and then it is developed and commercialized to create benefits for the individual or firm owning the idea. We used a SEM modeling framework to investigate the relationships among inventive activity and potential inventors, regional technology levels, and regional productivity outcomes. Our results show almost no significant direct relationship between invention and productivity, except through technology. Clearly, the simplification of the linear "invention in/productivity out" model does not hold, which supports other work that questions the use of patents and patenting related measures as meaningful innovation inputs to processes that generate regional productivity and productivity gains. We also find that the most effective measure of regional inventive capacity, in terms of its effect on technology, productivity, and productivity growth is the share of the workforce engaged in creative activities.

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