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Penetrating the Knowledge Filter in "Rust Belt" Economies

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Abstract

A new model of economic growth introduces the knowledge filter between new generic knowledge and economically-useful knowledge. It identifies both the formation of new ventures and the absorptive capacity of incumbent firms as the mechanisms that penetrate the knowledge filter. Recent empirical work has shown that new firms are more proficient at penetrating the knowledge filter than are incumbent firms; however, the analysis has only examined expanding economies and has relied on purely cross-sectional regression methodologies. This study explores the role of new and incumbent firms in penetrating the knowledge filter utilizing recent developments in spatial panel estimation techniques to provide a more robust set of findings. The results suggest that new firms are more proficient at penetrating the knowledge filter in declining and growing regions alike.

JEL-classification: L26, O1, O18, O3, R1

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1. Introduction

The production and application of new knowledge is often seen as pivotal to economic growth and prosperity. This idea, strongly voiced by endogenous growth theorists (Romer, 1990), forms the basis for several policies intended to rev the engine of economic progress. Included in these is the Bayh-Dole Act, enacted in 1980, which transfers to research performing universities the intellectual property rights to federally funded research as well as the Small Business Innovation Research (SBIR) program established in 1982.[1] These developments – coupled with deregulation, the biggest wave of merger and acquisition in U.S. history, pension fund reforms that gave rise to institutionalized venture capital, and the reorganization of most corporate R&D activities – have been followed by two decades of unprecedented economic dynamism with the emergence of new industries and the renewal of old ones (Acs and Armington, 2006).

Indeed, whereas in the early postwar period innovation tended to be carried out by large firms in capital-intensive, concentrated industries characterized by highly differentiated goods, the last two decades have been characterized by a different technological regime in which innovation is carried out primarily by new firms in highly knowledge and skilled-labor intensive industries having a large share of big firms (Winter, 1984; Acs & Audretsch, 1987; Plummer & Acs, 2005; Holtz-Eakin & Kao, 2003). Jovanovic, for example, finds that the performance of small companies vs. large ones (as measured by the price of small capitalization stocks relative to the S&P 500) is

[1] As important as Bayh-Dole was, it was essentially an attempt to "reverse engineer" the technology transfer process that had worked so effectively in prior years at a few very special institutions such as MIT and CalTech. In the face of the incentives offered by Bayh-Dole, a wide range of universities adapted to a new landscape and began promoting technology transfer, but the vast majority of them never developed the kind of permissive, entrepreneurial culture that marked the early models.

about equal from the end of World War II to the late 1960s and then rises dramatically to a 4:1 ratio by the mid-1980s (Jovanovic, 2001, p. 54).[2]

This structural transformation of the United States economy emphasizing the contribution of new firms suggests that the production and application of knowledge, although a necessary condition, is not sufficient alone for economic growth in local economies. Instead, it seems that any general knowledge available in the economy must be actively “converted” into economically useful knowledge and that this conversion is a particular specialty of new firms.[3] Moreover, the conversion of knowledge seems a highly localized process given evidence that the flow and diffusion of knowledge is spatially constrained (Anselin, Varga and Acs, 1997). As a result, the link between the production of knowledge and economic growth appears most evident at a regional level of analysis.

Acs, Audretsch, Braunerhjelm, and Carlsson conceive of the conversion of available knowledge into economically useful knowledge as the “penetration” of a “knowledge filter” by the actions of both new and existing firms. The knowledge filter is the sum of all the barriers inhibiting the conversion of knowledge produced by research into commercialized knowledge (Carlsson, Acs, Audretsch and Braunerhjelm, 2007). By characterizing the knowledge filter as being “semi-permeable”, Acs et al (2004) contend that the conversion of knowledge in regional economies occurs only through the

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[2] Jovanovic attributes this rise in the relative performance of small firms to the application of the microprocessor. He also notes that among the twenty largest U.S. companies by market capitalization in 1999, ten were incorporated in or after 1967.

[3] There are two reasons why this may be true: One, new firms may simply do certain things (such as certain types of innovation) better than large firms. As a result, through division of labor between small and large firms, the efficiency and growth of the economy is increased. Two, new firms are indicative of the entrepreneurship and variety required for particularly meaningful economic growth and stability (Carlsson, 1999).

concerted *actions* and the bearing of relevant costs by new and existing firms. Thus, the knowledge filter conjecture suggests that the contribution of knowledge to regional economic growth *depends* on the absorptive capacity of existing firms as well as the creation of new firms by individual entrepreneurs; Acs and Plummer (2005) find support for the conjecture using economic data for the state of Colorado.

The purpose of this paper is to test the knowledge filter model of endogenous growth in the context of *declining* regional economies. For the past 30 years, the performance of Colorado's economy has been exceptionally strong with a gross state product that has increasingly outpaced the national average. Over the same period, Ohio is a declining "rustbelt" region once dominated by large firms and heavy manufacturing with gross state products increasingly falling behind the national average.[4] The focus of this paper, then, is to ask, does the knowledge filter conjecture hold in declining local economies? Far from being a mere replication, this study carries important theoretical implications for the Acs et al (2004) knowledge filter model of endogenous growth and the Acs et al (2005) knowledge spillover theory of entrepreneurship model by serving to assess the validity and generalizability of the theoretical models.

The paper is organized as follows. Section 2 discusses the existing economic growth theory and outlines the basic assumptions regarding endogenous growth models. Section 3 lays out the basic elements of the model and develops the hypotheses to be tested. Section 4 describes the research design and section 5 reports the results of our analysis. Finally, section 6 will provide some conclusions.

[4] The manufacturing "rust belt" of the United States covering many of the Great Lakes states including Ohio experienced a dramatic decline from the early 1970's well into the 1980's characterized chiefly by "deindustrialization" (High, 2003). Among the monumental shifts in these regional economies were large reductions in manufacturing employment, plant closures, rising crime rates, and net population losses.

2. Endogenous Growth

The pivotal contributions of Romer (1986, 1990), Lucas (1988), and their followers to the theory of economic growth are celebrated. Their efforts theoretically endogenize the production of knowledge within an economy and thereby disconnect growth from investment in physical capital or increases in the supply of labor. The model has the following basic structure: At the firm-level, knowledge is produced by profit-maximizing firms, while at the macro-level, the production of knowledge has important implications for growth. In Romer's original formulation, knowledge enhances growth in two ways: First, the knowledge-producing firm runs its operations more efficiently, and, second, the produced knowledge spills over to other firms, acting as a shift factor in their production functions. In subsequent variants, referred to as Schumpeterian growth models, economic growth is propelled by the combination of competition and temporary monopoly profits stemming from knowledge-based innovations.

The endogenous growth models provide little micro-economic foundation for explaining the mechanisms that promote growth at the macro-level. In other words, the focus is chiefly on growth at the national level. As applied, however, the emphasis in these models is often on the macro-economic consequences of innovation and knowledge. As Acs et al (2004) contend, the simplistic firm-level formulation of endogenous growth models misguides policy-makers and makes empirical testing and validation of the models much more difficult. In this vein, Acs et al (2004) explore the underlying assumptions of the basic endogenous growth model intended to better capture how and why knowledge contributes precipitously to economic growth.

2.1 Assumptions on Firms and Technology

Endogenous growth models rely on several assumptions regarding the nature of the firms themselves and the production technology they employ. In the case of the former, for example, the model builds on the assumption of a "representative" firm intended to capture firm-level behavior at a macroeconomic level of analysis.[5] As for production technology, it is generally assumed that the *production of goods* is characterized by increasing returns to scale as a function of the increasing marginal productivity of knowledge, but the *production of knowledge* is subject to diminishing returns to scale.[6] Given the these assumptions, there is an optimal level of knowledge for the firm to produce and thus, all things equal, an optimum rate of growth.

2.2 Assumptions on Knowledge

A particularly important, and often problematic, set of assumptions concerns the nature of knowledge. In particular, it is typically assumed that firms employ *firm-specific knowledge* in the production of goods. The knowledge produced exists forever in a non-depreciating stock implying that zero research by a firm means that the firm's stock of knowledge is constant. The assumption of firm-specific knowledge serves an important theoretical purpose, but is somewhat inconsistent with assumptions previously mentioned. Indeed, if "representative" firms are symmetric – i.e., the same size and producing the same goods, etc. – why then is firm-specific knowledge necessary? The answer is that the assumption of firm specificity is necessary to justify that only a *portion*

[5] In particular, the scale and number of firms are indeterminate and all are assumed to be price-takers implying that many firms are operating in a competitive market and are earning zero profits. In addition, the number of firms is given, all firms operate at the same output level, and either no start-up of new firms occurs (in the Romer model) or new products are introduced through R&D races (in the neo-Schumpeterian models).

[6] On the firm level, empirical evidence demonstrates a concave relation prevails between firm performance and knowledge investment (Braunerhjelm 1999).

of the knowledge produced by a firm spills over to another. This assumption is necessary for the dynamics of the model, but seems inconsistent with other firm-level assumptions.[7]

2.3 Assumptions on the Spatial Distributions of Knowledge

Perhaps the most crucial assumption in the theory of endogenous growth is that the total stock of knowledge produced by firms is evenly distributed across geographic space. This assumption, however, is not supported empirically in the literature on geographic knowledge spillovers. Complex technological knowledge (seemingly the most valuable type of knowledge) usually contains a strong element of tacitness meaning its flow and diffusion is constrained by the geographic proximity and extent of interaction among individuals within whom the tacit component resides. A host of recent empirical studies have confirmed that knowledge spillovers are geographically bounded (Jaffe 1989, Jaffe, Trajtenberg and Henderson 1993, Audretsch and Feldman 1996, Anselin, Varga and Acs 1997, Keller 2002).

2.4 The "Missing Link"

Endogenous growth models do not adequately explain knowledge spillovers accruing from aggregate knowledge investment. Even in the Schumpeterian models, entry is restricted to existing firms investing in R&D that comply with the behaviors assumed of incumbents. In essence, at the firm-level, knowledge spillovers occur automatically without regard to the absorptive capacity of firms or the entrepreneur's ability and actions. The condition imposed by the discussed assumptions lacks both theoretical and intuitive appeal as well as empirical backing. Indeed, it is one thing for technological

[7] As Acs et al (2004) point out, if knowledge at the firm level was identical any subsequent spillovers would be direct and involve 100 percent of the produced knowledge. If this were the case, other firms would have no incentive to invest in the production of knowledge resulting in no, or at least less, growth.

opportunities to exist, but an entirely different matter for them to be discovered, exploited and commercialized (Acs and Varga, 2002).[8]

3. The Knowledge Filter Model

The term "Schumpeterian" growth model already implies some of the mechanisms deemed missing from the basic endogenous growth model: innovative entry, the reorganization and rationalization of existing firms, and firm exits as the result of "creative destruction" (Schumpeter 1911, Hayek 1945). Although these factors are implied, they must be better and explicitly integrated theoretically into the endogenous growth process in order to capture the interdependency between knowledge, opportunity, and commercialization. In particular, newly produced knowledge – embodied in patents, products, processes, organizations and the like – defines opportunities that can be exploited commercially. With that said, for new ideas to translate into economic growth, new knowledge must be converted into what Kenneth Arrow (1962) identified as economic knowledge.

3.1 The Knowledge Filter

The most fundamental argument made by Acs et al (2004) is that knowledge by itself is a necessary, but not sufficient, condition for economic growth. Michelacci (2003), for example, focuses on the allocation of societal resources spent on R&D and entrepreneurship and concludes that that low rates of return to R&D may be due to lack of entrepreneurial skills. Thus, the ability to transform new knowledge from economic opportunities to growth-improving products and processes involves a set of skills,

[8] Acs and Varga (2002) suggest that if one is to understand endogenous economic growth one needs to answer the question of how technological advance occurs, and what are the key processes and institutions involved.

aptitudes, insights and circumstances that is neither uniformly nor widely distributed in the population. This suggests that the conversion of new knowledge into economic knowledge occurs with the expenditures both tangible and otherwise (e.g., effort) of relevant economic agents.

Complicating the knowledge conversion process are the uncertainty, asymmetries, and high transactions cost making it difficult to evaluate the expected value of new ideas; indivisibilities in the production of knowledge; and limits to the appropriation of any expected returns (Arrow, 1962). Acs et al (2004) conceive the combination of barriers to converting new knowledge (produced by research activities) into economic knowledge as the "knowledge filter." This knowledge filter is conceptualized as being "semi-permeable" in the sense that the collection of obstacles to the knowledge conversion process can be overcome with the effort and actions of firms and individuals.

3.2 "Arrowian" Conversion of Knowledge

As Romer (1990) assumes, new knowledge is a non-rivalrous and partially excludable good. Such new knowledge, however, passes through an "Arrowian" conversion process that determines the rate at which the stock of knowledge (K) is converted into economically useful firm-specific knowledge (K^c), $0 \leq K^c / K < 1$. In addition, knowledge spillovers are spatially (regionally) bounded and access to any localized stock of knowledge is assumed to be equal to all local entities. There are two mechanisms by which new knowledge (K) is converted into economically useful knowledge (K^c). The first involves incumbent firms, $K^{cI,}$ and the second involves the entrepreneurial startup of new (Schumpeterian) firms, K^{cSch},

$$K^c = K^{cI} + K^{cSch}. \tag{1}$$

As a result, the conversion of economic knowledge from new knowledge is based on the combination of the absorptive capacity of incumbent firms (θ) and the propensity for entrepreneurship in the local economy (λ). Policy and previous history (path dependence) in the form of regulations, attitudes, networks, and technology transfer mechanisms determine the absorptive capacity (θ) of incumbents and the region's propensity for entrepreneurship (λ),

$$K^c = (\theta + \lambda)K, \quad 0 \le \lambda + \theta < 1. \tag{2}$$

3.3 Incumbent Firms

Incumbent firms transform knowledge as a function of their absorptive capacity (Cohen and Levinthal, 1990). In particular, a firm converts new knowledge into economically useful knowledge, K^{cI}, by a combination of investing in R&D and learning-by-doing; these activities add to the firm's firm-specific knowledge. The firm's absorptive capacity to exploit spillovers, which we denote θ, depends at each given point in time on previous accumulation of firm-specific knowledge $k_{i,t}^{I}$,

$$k_{i,t}^{I} = f(\int_{t=0}^{t} k_{i,t}^{I} dt, K), \quad \sum_{i}^{n} k_{i,t}^{I} = K_t^I, \quad K_t^{cI} = \theta\, K, \quad \theta < 1 \tag{3}$$

Given this perspective, we propose,

> Hypothesis 1: The contribution of newly created knowledge in a region to economic growth depends on the absorptive capacity of incumbent firms in a region.

3.4 New Firms

A set of individuals S can either be employees in the production of goods (L_M) or knowledge (L_R), or become entrepreneurs (L_E). Entrepreneurial ability is distributed unevenly across individuals; these individuals deploy their endowments of entrepreneurial capabilities to evaluate the new knowledge available to them and decide how best to appropriate the returns from that knowledge. Individuals make profit-maximizing inter-temporal choices whether to remain an employee or become entrepreneurs (Knight, 1921).

Entrepreneurial start-ups are the manifestation of the knowledge transformation process. In short, each start-up represents a new idea (innovation), which represents any kind of new combination of new or existing knowledge, where individuals draw on their entrepreneurial ability ($\bar{e}_i$) and the aggregate stock of knowledge (K).[9] Start-ups occur through a Poisson process, which leads to the successful entry of a share λ of new firms,

$$K^{cSch} = \lambda\ K, \quad \lambda < 1. \tag{4}$$

Thus, we contend,

> <u>Hypothesis 2</u>: The contribution of newly created knowledge in a region to economic growth depends on the propensity of a region to create new business ventures.

3.5 Incumbent versus New Firms

Aspects of the knowledge filter – especially those concerning the evaluation and assessment of the future expected values – have particularly perverse effects within established firms. In particular, there are strong disincentives for incumbent firms to invest in the production of new knowledge at socially-optimal levels and/or deploy truly novel knowledge. There is, for example, a concern that new products will "cannibalize" revenue streams of existing ones or that the minimum required investment in R&D is, due to indivisibilities in the production of knowledge, too great (Bernard, Redding, and

[9] Schumpeter (1911).

Schott, 2006). Thus, there is the possibility that the knowledge passed over by existing firms may be deemed “too risky” or “too revolutionary” to merit investment. As a result, the decision-making process within incumbent firms can induce agents to start new firms as a mechanism to appropriate the (expected) value of new knowledge.

Indeed, empirical findings suggest that entrepreneurial startups are important links between knowledge creation and the commercialization of such knowledge, particularly at the early stage of the firm or innovation lifecycle when knowledge is still fluid (Utterback and Abernathy, 1975). Thus, by serving as a conduit for the spillover of knowledge that might not otherwise be commercialized by incumbent firms, entrepreneurship is the mechanism most likely constituting the strongest link between knowledge and economic growth (Acs, et al, 2005). Thus,

> Hypothesis 3: The contribution of newly created knowledge to economic growth in a region depends more strongly on newly created business ventures than on the absorptive capacity of existing incumbent firms.

3.6 Booming versus Declining Economies

As mentioned, Acs and Plummer (2005) find support for the knowledge filter conjecture using cross-sectional county-level data covering 1990 to 2000 gathered for the state of Colorado. The pressing issue that this study addresses is that these received findings constitute support for the model in a particular context. Assessing the generalizability of the model, while primarily an empirical exercise, is critical to validating the knowledge filter model as conceived. Economic growth is itself somewhat self-fulfilling in that the expansion of incomes and increases in standards of living carry forward from year to year in a way vital to an economy's future prosperity (Henderson, 2003).[10] Given this perspective, it is essential to theoretically validating the knowledge filter model to test the central conjecture in the context of diminishing economic conditions. This is the theoretical basis for our focus on the state of Ohio.

4. Research Design

4.1 Sample and Data Collection

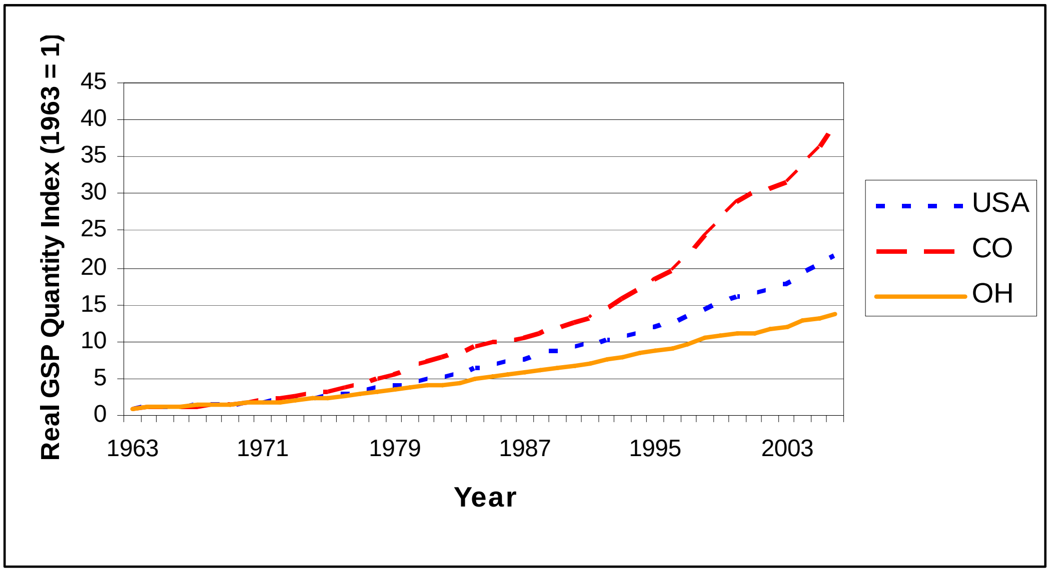
Aside from the theoretical basis discussed above, the sample of Ohio counties is based on criteria suggested by Acs and Plummer (2005) and the data are collected to afford comparability with their analysis. In particular, the sample for this study contains adequate variance in the variables in the model and encompasses counties large enough to represent statistically workable regions of knowledge spillovers. The period of the current study is 1990 to 1999 comparable to Acs and Plummers' 1990 to 2000 study period. Data for the year 2000 was not included here because county-level patent data for Ohio was not available for that year. As detailed in the next section, the data came from the U.S. Census Bureau, the U.S. Patent and Trademark Office, the Bureau of Economic Analysis (BEA), the Small Business Administration (SBA), and the National Science Foundation (NSF).

Ohio, comprised of 88 counties, is a mid-western state with a rich history of industrial dominance and, in contrast to Colorado, has experienced economic decline in recent decades. As shown in Figure 1, Ohio's gross state product kept pace with the United States average until 1979 and began to lag considerably thereafter. Colorado, by

[10] Henderson (2003) finds that these effects carry forward between five and twenty years depending on the industry structure of the local economy.

comparison, began to surge ahead in 1975 with a slight retraction toward the national average during the recession of the early 1990's. After that period, Colorado surged

Figure 1. Annual Change in Real Gross State Product 1963-2006



Source: Bureau of Economic Analysis, U.S. Department of Commerce

strongly ahead of the U.S. average with a minor retraction after 2000. Over the period 1963 – 2006, Colorado's real GSP increased by a factor of over forty while Ohio's real GSP increase was far more modest. In addition, personal income growth in Ohio after 1982 lagged behind the United States in general and the state of Colorado in particular. Likewise, manufacturing output declined in Ohio by 20 percent from 1978 to 1983 and never again exceeded its 1978 level of output until the early 1990s. This makes the state of Ohio an appropriate context in which to examine the knowledge filter model.

4.2 Variables

The variables for this study are defined in a manner consistent with Acs and Plummer (2005). This facilitates a comparison of the current studies' results to those found in their study.

Personal Income Growth: The dependent variable is calculated from data obtained from the Bureau of Economic Affairs regional economic accounts. Personal income growth is the annual change in personal income from one year to the next.

Knowledge: Knowledge is notoriously difficult to measure and little data beyond patent counts exists as a county-level measure. As a result, in this paper we measure the county's stock of knowledge as the number of patents granted in a given county using data obtained from the U.S. Patent and Trade Mark Office. For standardization purposes, the number of patents granted is divided by the total number of establishments in the given county.

Research and Development: Since patents capture the output from knowledge production activities in the county, we include an indicator of research and development activities in a given county. Information on research and development *expenditures* is not available at the county-level. Thus, as an alternative, we assigned a dummy code equal to 1 to the counties with universities, federally funded R&D centers, and non-profits receiving federal R&D funding sometime between 1990 and 1999. The dummy code equals 0 in those counties receiving no federal funding in the period. The data for this variable came from the National Science Foundation.

New Ventures: We define new ventures as number of "high technology" single-establishment births in the county divided by the number of existing establishments. The Census defines a single establishment as a single physical location where business is conducted or where services or operations are carried out.[11] The "high technology" sectors are defined using Varga's (1998) three criteria: industries with (1) an above

[11] A single-establishment birth for a given year is defined as an establishment having no payroll anytime the prior year and positive payroll in the first quarter of the current year.

average research and development to industry sales ratio at the 3-digit SIC level, (2) an above average percentage of mathematicians, scientists, engineers and engineering technicians compared to total industry occupations, and (3) the total number of innovations per 1,000 employees. The single-establishment birth and existing establishment data were obtained from the U.S. Bureau of the Census. The establishment birth tabulations are broken out by year, by Standard Industrial Classification code (SIC) for 1990-1997 and by North American Industrial Classification System (NAICS) for 1998-1999 at the four and five digit levels, respectively.

Incumbents: The number of establishments with more than 100 employees divided by the total number of establishments is our measure for incumbent firms. This proxy measure is used due to the lack of information in the Census data regarding the establishment's age. Age and size are generally correlated and it seems unlikely that a single establishment firm would start out with 100 or more employees.

Density: Density is defined as the total number of establishments in a given county divided by the county's total area in square miles. It is included to capture the relevant effects of the geographic concentration of economic activity, resources, and people. The data for the numerator and denominator in this variable were obtained from the U.S. Census Bureau.

Log Total Personal Income: Using the BEA regional accounts, we include the log of total personal income in the county to account for the possibility that subsequent growth is likely a function of previous wealth. Furthermore, the inclusion of the logged level of total personal income facilitates inferences regarding the notion that richer economies grow more slowly (Barro, Sala-I-Martin, Blanchard, and Hall, 1991). Stated another way, the logged value of total personal income is included as an explanatory variable to account for variation in the dependent variable resulting from higher initial income levels. The convergence hypothesis predicts a negative coefficient estimate for this variable.

Interaction Terms: The last two variables included in this analysis embody the interactions of knowledge with new and incumbent firms. These variables constitute the primary variables of interest in this study as all of the proposed hypotheses employ the crucial proposition that the production of knowledge is a necessary yet insufficient condition for achieving economic growth. The inclusions of these two variables provide a means for testing this important concept; therefore, specific emphasis will be placed on the inferences supplied by these variables.

4.3. Estimation Issues

There are a number of relevant regression issues that must be diagnosed when carrying out regression modeling of economic growth. These issues are spatial dependence, heteroscedasticity and outliers, as well as collinearity. These statistical problems are particularly important because the existence of spatial dependence has been shown to be a source of both bias and inefficiency under traditional regression methodologies such as OLS (Anselin, 1998; LeSage, 1997). When the dependent variable vector exhibits spatial autocorrelation, the resulting parameter estimates are known to be biased; where as when the spatial dependence is contained simply in the residuals, the problems involve only efficiency (Anselin, 1998; LeSage, 1997). Therefore, the particular structure of the spatial dependence existing in the sample data governs which type of spatial regression model ought to be employed in one's empirical pursuits.

Heteroscedasticity is a concern because its existence is known to cause inefficiency whereas outliers have been shown to cause bias in the resulting parameter estimates. Lastly, collinearity is a common problem in regression modeling and is associated with an over estimation of standard errors and, hence, is a problem with regard to efficiency. As well, a lack of consistency in the magnitudes and significance levels of the parameter estimates is commonly associated with datasets suffering from collinearity.

4.3.1. Spatial Dependence

We expect that the dependent variable, personal income growth, exhibit spatial dependence. Spatial dependence becomes an issue when observations at one location, y_i, depend on neighboring observations, y_j, where j denotes the set of neighboring observations to any observation, y_i. The existence of spatial dependence invalidates the use of ordinary least-squares (OLS) regression methods (LeSage, 1997) and requires that we apply an alternative estimation procedure.

To assess and account for this statistical problem, we employ diagnostic test statistics, such as Moran's I, as well as spatial regression methodologies that investigate the particular nature of the dependence relationship and explicitly deal with its existence. To carry out this analysis we began by testing for the existence of spatial dependence using the test statistic commonly referred to as Moran's I. Moran's I provides a statistical procedure for testing for the existence of spatial autocorrelation, however, the test provides no means of correcting for this problem. Estimating a spatial autoregressive regression model provides both a test for the existence of spatial dependence among the dependent variable observations as well as it provides a means of accounting for this problem, should it exist.

If the estimation of this type of regression model reveals that the spatial dependence parameter, ρ, is statistically significantly different from zero, then one can conclude that spatial dependence exists amid the n x 1 vector of dependent variable observations. Upon estimation of this type of regression model, one can then analyze the resulting residuals to examine whether or not spatial autocorrelation remains in the residuals. This can be carried out via either Moran's I or the Wald statistic or by estimating a spatial error regression model (SEM). These procedures provide a simple way of investigating whether or not the spatial autoregressive regression model adequately deals with the spatial dependence inherent in this particular application or whether a spatial error model or even a general spatial regression model[12] ought to be utilized.

4.3.2. Heteroscedasticity and Collinearity

To take into account possible heteroscedasticity in the data, we rely on the estimation of a Bayesian heteroscedastic linear variant of the spatial autoregressive model that is robust to both outliers and heteroscedasticity (LeSage, 1997). By comparing robust and standard SAR results, we can determine if heteroscedasticity and outliers are a concern in the data. Supposing that heteroscedasticity exists, we would observe an increase in the t-statistics associated with the coefficient estimates resulting from the Bayesian heteroscedastic linear variant of the SAR model when compared to the traditional SAR model's coefficient estimates. The existence of outliers would cause the two estimation

[12] The use of the term general spatial model pertains to a particular spatial regression model that incorporates spatial autocorrelation amongst both the dependent variable observations and residuals. It is described as a general spatial model due to its generalization of both the spatial autoregressive regression model and the spatial error regression model (LeSage, 1998). It should be relied on when the spatial dependence structure is more complex than assumed by both the SAR and SEM models, and as a result, when spatial correlation exists in the residuals associated with the estimation of a SAR model.

routines to produce coefficient estimates that differ in magnitude on a scale dependent on the extent and size of the outliers. Therefore, if the estimation of these two regression models produce coefficient estimates that are statistically equivalent to each other, along with similar t-statistics, then one can conclude that neither heteroscedasticity or outliers are a problem with regard to the given sample data.

White or Breusch-Pagan tests are commonly used for determining these matters. However, these test statistics are considerably less valuable than is the above strategy for a number of reasons. For one, these test statistics commonly fail to provide the proper inferences. As a result, the use of these methods commonly provides incorrect information. For example, suppose one is presented with a situation where the White test statistic is used and is statistically significant at only the 85 percent-level. The general approach would be to imply that since the White test-statistic is not statistically significant at least at the 90 percent-level, then one cannot reject the null hypothesis that there exists no heteroscedasticity. However, how is one to know whether or not any bias or inefficiency exists in subsequent least-squares parameter estimates? The short answer is they simply do not know. The common approach is to simply imply that, since the test-statistic is not statistically significantly different from zero, the impacts associated with heteroscedasticity are not influential. However, there is little basis for that conclusion other than the rules of thumb associated with this testing procedure. As well, test-statistics only indicate whether or not the problem exists, thus, providing nothing for correcting for these problems.

The strategy relied on in this paper is substantially better than relying on information provided by test statistics. The reasons for this are that this procedure is:

1. Capable of diagnosing whether or not a systematic heteroscedastic trend exists across the observations in the sample or whether the particular heteroscedasticity takes on the form of a few significant outliers.
2. This procedure provides a means of identifying the extent of the influence of these problems on the resulting parameter estimates.
3. This procedure provides a means of correction should heteroscedasticity (in either form) exist in the sample data. The use of a testing procedure completely fails in this regard.

To test for the presence of collinearity problems we subject the sample data to the Belsley, Kuh, and Welsch collinearity diagnostic, which lends a variance-decomposition proportions matrix (Belsley et al., 1980). Secondly, we implement a method of estimating ten alternative specifications of each regression model, where the alternative specifications are based on different specifications of the matrix X. Stability in the parameter estimates and significance levels across the different permutations mitigates problems associated with lack of precision, as one can draw inferences from commonalities across the alternative specifications of the regression models. Furthermore, the spatial panel estimation procedures, laid out in Section 4.5, further mitigate any existing collinearity that may linger in the sample data (Elhorst, 2003).

4.4. Spatial Autoregressive Model

To test for the influence of spatial dependence across the observations in our sample, we estimate a spatial autoregressive (SAR) model of the following form[13]:

[13] This particular spatial regression model was initially utilized because previous empirical work (Acs and Plummer, 2005) demonstrated that spatial dependence existed amongst the vector of dependent variable observations. Therefore, it was determined that bias in the resulting parameter estimates was a bigger problem than was inefficiency. However, the residuals stemming from estimating this regression model

$$y = \rho Wy + X\beta + \varepsilon \quad (5)$$
$$\varepsilon \sim N(0,\sigma^2 I_n)$$

W denotes an 88 x 88 spatial weight matrix that defines the set of neighboring counties to each observation. ρ denotes a scalar parameter measuring the strength of the relationship between the dependent variable, y_i, and the spatially lagged variable vector, Wy_i. It is important to note here that inferences regarding the existence of spatial dependence are, then, provided by the coefficient estimate of ρ. If ρ is non-zero and is statistically significant, then the existence of spatial dependence is confirmed to exist in the sample data. In this situation SAR and OLS parameter estimates should differ as OLS parameter estimates are biased in the face of spatial dependence.

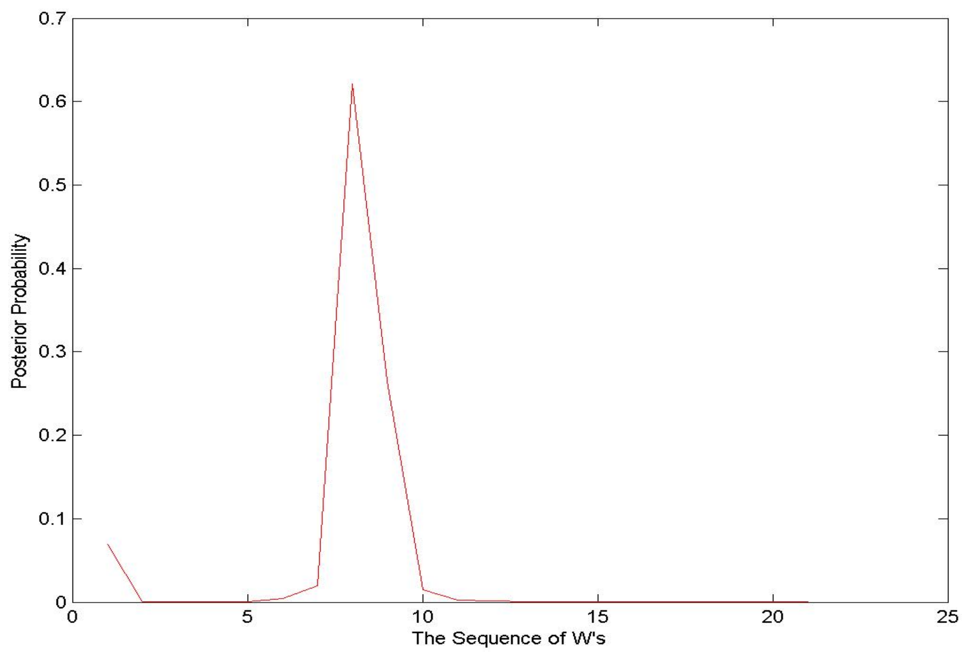
A variety of approaches have been used to define *W* with the most common being a first order contiguity-based specification. To help validate our definition of the spatial weights matrix, we specify a set of twenty-one row-standardized spatial weights matrices. The set of alternative weight matrices are based on (1) a first-order contiguity based specification and (2) on a sequence of 20 weight matrices that are specified to select one through twenty of the nearest neighboring counties, respectively. We select the weights matrix associated with the largest posterior model probability, thereby, selecting the weights matrix that "best" fits the sample data.[14] It should also be noted here that the selection of this sequence of weight matrices was initially quite ad hoc, for a one could specify many more such matrices; all the way up to specifying one that selects every observation, that being one that selects the 88 nearest neighbors. However, inspection of the posterior model probabilities associated with these weight matrices revealed that

revealed that no significant spatial correlation remained in the residuals and, hence, the estimation of a spatial error model was unnecessary at that point.

[14] This was accomplished using LeSage's (1998) "sar_g" and "model_probs" Matlab functions.

specifying this matrix to extract a larger number of neighboring observations than this tended to decrease the posterior model probability, indicating that our sequence was more than adequate. This fact is demonstrated in Figure 2, where the first specification is one based on first order contiguity while the others are the 1 through 20 nearest neighboring specifications.

Figure 2. Posterior Model Probabilities for the Sequence of W's



4.5. Spatial Panel Data Models

Spatial panel regression models provide several important advantages when compared to their cross sectional equivalents. For one, the reliance on our panel of data significantly increases the number of observations underlying the inquiry (going from 88 observations in the cross-sectional analysis to 880 observations when relying on our 10 year panel), thereby, providing a considerable increase in precision and robustness. Secondly, the spatial panel routines are known to help extinguish the impacts of any undetected collinearity that may exist in the sample data (Elhorst, 2003). As a result, we exploit the advantages of our panel data by estimating two panel data equations. The first (Equation 6) is a pooled model with the inclusion of a spatially lagged dependent variable. The second (Equation 7) is a pooled model that includes a spatially lagged dependent variable as well as time fixed effects.

The specification of Equation 7 is based on three factors. First, random effects are inappropriate when observations are based on irregular spatial units such as counties (Elhorst, 2003; Anselin, 1988). Second, the assumption of zero correlation between μ and X in the random effects model is restrictive and unlikely to hold. Lastly, we exclude spatial (i.e., county) fixed effects because spatial fixed effects cannot be consistently estimated (Elhorst, 2003).[15] In contrast, time fixed effects can be consistently estimated. The two equations – with W the row standardized first order contiguity weighs matrix described above – take the form:

$$y_t = \rho W y_t + X_t\beta + \varepsilon_t \qquad (6)$$
$$\varepsilon_t \sim N(0,\sigma^2 I_n)$$

and

$$y_t = \rho W y_t + X_t\beta + \mu + \varepsilon_t \qquad (7)$$
$$\varepsilon_t \sim N(0,\sigma^2 I_n)$$

These equations are estimated by first demeaning the Y and X variables such that the Y and X variables for each spatial unit are expressed in deviation from their average over time (Elhorst, 2003). Given the inclusion of the spatial lag and the resulting statistical complications, we use a two stage procedure, with the intercept estimated as β_1

[15] In our panel, T = 10 and N =88. In this spatial panel context, T can be viewed as fixed while N tends towards infinity (in other words, N is considerably larger than T). Thus, only time fixed effects can be consistently estimated.

+ μ_i (Anselin 1988, 181-182), to maximize the log-likelihood function (Elhorst 2003, 250) resulting in maximum likelihood estimates (MLE) of the relevant parameters.[16]

5. Results

5.1 Descriptive Statistics and Correlations

Table 1 contains descriptive statistics associated with the 10-year annual averaged variables. Row 1 of Table 1 contains the dependent variable, the average annual growth rate of total personal income. As can be seen from the table, the average annual growth

Table 1. Descriptive Statistics

Variable	Mean	STD	Min	Max
Total Personal Inc.	0.047	0.011	0.028	0.108
Density	6.545	12.524	0.362	79.13
LogTotInc	14.071	1.103	12.029	17.42
Knowledge	0.008	0.007	0.001	0.036
RDdummy	0.125	0.333	0.000	1.000
NewVentures	0.002	0.001	0.000	0.006
Incumbents	0.023	0.006	0.011	0.039

rate of county-level total personal income was approximately 5%. The minimum value was around 3%, occurring in Noble County in South East Ohio, while the maximum was approximately 11% occurring just North of Columbus, Ohio in Delaware County.

As for the independent variables, the mean density was 6.55 establishments per square mile with a standard deviation of 12.52, indicating considerable variability in the density of Ohio’s counties. The minimum density occurred in Vinton County Ohio, located in South East Ohio, while the maximum density occurred in Cuyahoga County, the county containing Cleveland, Ohio. The mean value of the log of total income was 14.07 with a standard deviation of 1.10. Cuyahoga County was associated with the maximum value while Vinton County was associated with the minimum value. There is

[16] The models were estimated using the “sar_panel” Matlab function (Elhorst, 2003).

on average eight patents per 1,000 establishments with a range of 1 patent per 1,000 establishments, occurring in Belmont County Ohio along the South East border, to 36 patents per 1,000 establishments, occurring in Delaware County Ohio, North of Columbus, Ohio. On average, there were 2 new high technology ventures per 1,000 establishments, within a range of 0 to 6 per 1,000 establishments. The maximum value, again, occurred in Delaware County Ohio. On the contrary, there were 23 incumbent firms per 1,000, with a range of 1.1 to 39 incumbents per 1,000 establishments. The minimum value was again located in the South East region of the state, in Vinton County, while the maximum value occurred in Shelby County Ohio, located in West Central Ohio.

Table 2 reports the correlations among the variables. All of the explanatory variables except density, log total income, and incumbent firms were positively correlated with total personal income. Knowledge was most correlated with total personal income growth (0.542) while the log of total personal income was the least correlated with this variable (-0.033). Interestingly, new ventures showed the strongest correlation with knowledge (0.768) while density (0.227) and incumbents (0.268) showed the weakest correlations with this variable.

Table 2. Correlation Matrix

Variable	1	2	3	4	5	6	7
1. Total Personal Inc.	1.000						
2. Density	-0.169	1.000					
3. LogTotInc	-0.033	0.786	1.000				
4. Knowledge	0.542	0.227	0.470	1.000			
5. RDdummy	0.106	0.558	0.472	0.336	1.000		
6. NewVentures	0.484	0.439	0.632	0.768	0.386	1.000	
7. Incumbents	-0.043	0.349	0.420	0.268	0.316	0.303	1.000

5.2 Heteroscedasticity, Outliers, Collinearity and Spatial Dependence

We find that heteroscedasticity and outliers are not influential factors in the data. This is due to the fact that the coefficient estimates produced by the SAR and Bayesian linear heteroscedastic SAR model are statistically equivalent to each other (based on a t-test between the two sets of coefficient estimates). If outliers were of statistical importance then the coefficient estimates produced by the estimation of a SAR model would be statistically significantly different from the coefficient estimates produced by the estimation of the robust Bayesian linear heteroscedastic SAR model (LeSage, 1997). Furthermore, the fact that these two models produce asymptotic t-statistics of similar magnitude, yielding the exact same inferences, renders a situation where one can confidently infer that systematic heteroscedasticity across the sample observations is not a significant problem in our sample. Therefore, we only present the SAR results as no additional information was provided by estimating the Bayesian linear heteroscedastic SAR model.

The presence of collinearity was investigated in two ways. First, the data was subjected to the Belsley, Kuh, and Welsch (BKW) collinearity diagnostic. This technique is based on the singular value decomposition, where this decomposition is applied to the variance-covariance matrix of our OLS estimates and is rearranged to create a variance-decomposition proportions matrix, which is shown in Table 3 (Belsley, Kuh, and Welsch, 1980).

The first column contains the condition indices while the other columns contain variance-decomposition proportions. The joint condition of a condition index greater than 30 along with a variance-decomposition proportion in excess of 0.5 indicates the possibility of collinear relations amongst the associated variables (Belsley, Kuh, and Welsch, 1980).

Table 3. Belsley Kuh and Welsch Collinearity Diagnostic Results

Condition Index	Knowledge	Rddummy	NewVentures	Incumbents	Density	LogTotInc	K*NV	K*Incumb
1	0.00	0.00	0.00	0.00	0.13	0.01	0.00	0.00
2	0.00	0.00	0.00	0.00	0.41	0.02	0.00	0.00
63	0.00	0.88	0.00	0.00	0.22	0.00	0.00	0.00
2426	0.03	0.07	0.00	0.01	0.00	0.05	0.00	0.00
3216	0.00	0.01	0.00	0.43	0.00	0.34	0.00	0.00
14567	0.11	0.01	0.01	0.04	0.00	0.01	0.45	0.00
44307	0.35	0.01	0.55	0.08	0.03	0.40	0.49	0.31
49397	0.51	0.01	0.45	0.45	0.22	0.17	0.07	0.69

As is evident by examination of Table 3, there is only one instance where this joint condition is satisfied. The respective instance is located in the bottom row of this Table and pertains to the knowledge variable and the knowledge-incumbent interaction term. Here, one can observe that the variance-decomposition proportion associated with knowledge just barely exceeds the BKW threshold, while the proportion associated with the knowledge-incumbent interaction term definitely exceeds it. As a result, this evidence suggests that collinearity is not a significant problem with regard to our sample data; however, it does suggest that the knowledge and knowledge-incumbent interaction terms may suffer from this problem to a minor degree. Although the BKW evidence suggests that the influence of collinearity is slight, we relied on a method of estimating a set of alternative specifications of the regression model, that are based on alternative permutations of the explanatory variable matrix, to be on the safe side. Furthermore, our usage of spatial panel techniques, below, will work to overcome any lingering collinearity, should its existence produce any significant effects on our coefficient estimates in the first place (Elhorst, 2003).

Evidence supporting the existence of spatial dependence in the sample data comes from the computation of Moran's I, which is approximately equal to a value of 0.35 in this application. The t-statistic associated with this value is 6.12, which is clearly large than the 99% critical value, yielding a marginal probability level of 0.000. This evidence provides a clear indication of statistically significant spatial dependence.

As a result, OLS results are not presented as the existence of spatial dependence has been established by Moran's I, as well as below in Table 3, where the coefficient on the spatial dependence parameter, ρ, is positive and statistically significant at the 99 percent level in all specifications of the model. In light of this finding, OLS estimates are not to be relied upon as spatial dependence has been shown to exist in the sample data (LeSage, 1997).

Lastly, the model comparison techniques utilized to ascertain the most appropriate specification of the spatial weights matrix indicated that a weights matrix selecting the 7 nearest neighboring observations was associated with the largest posterior model probability and, hence, this specification of the spatial weight matrix was utilized in every instance where a W was required (see Figure 2 above).

5.3 Spatial autoregressive results

Three sets of results, obtained from estimation of the maximum likelihood SAR regression equation (Eq. 5) are reported in Table 4. Column 2 of Table 4 contains a Model 1 including all of the variables, except the interaction terms, discussed in Section 4.1. Column 3 contains a Model 2 that includes the interaction terms, while omitting new and incumbent firm variables. Column 4 contains a Model 3 that includes all of the variables discussed in Section 4.1.

Table 4. Maximum likelihood spatial autoregressive results

1990 – 2000 (average) Ohio Counties (N = 88)	Model 1 (r^2 = 0.53)	Model 2 (r^2 = 0.60)	Model 3 (r^2 = 0.60)
Constant	0.064***	0.053***	0.057***
	(3.940)	(3.540)	(3.718)
Knowledge	0.525***	0.317	0.327
	(3.291)	(0.753)	(0.641)
Rddummy	0.002	0.000	0.001
	(0.934)	(0.133)	(0.257)
NewVentures	6.226***		1.873
	(4.635)		(1.123)
Incumbents	-0.276***		-0.024
	(-2.168)		(-0.137)
Density	-0.000**	-0.000*	-0.000**
	(-2.473)	(-1.835)	(-1.948)
LogTotInc	-0.004***	-0.003**	-0.003***
	(-3.037)	(-2.490)	(-2.615)
K*NV		3.090***	2.578***
		(5.576)	(3.621)
K*Incumb		-1.678	-1.579
		(-1.431)	(-0.946)
Rho	0.622***	0.608***	0.612***
	(6.736)	(6.543)	(6.670)

Significance: '*' at the 90% level, '**' at the 95% level, and '***' at the 99% level - t-statistics are shown in parentheses

Examination of the results obtained from estimation of Model 1 indicates that knowledge and new high technology business ventures have positive and statistically significant impacts on the average annual growth rate of total personal income. Density and the log of total personal income are associated with negative and statistically significant impacts on the growth rate of total personal income. Incumbent firms are associated with a negative and statistically significant parameter estimate. The spatial dependence parameter, ρ, is quite large (it ranges from 0 to 1) and is statistically significant. This last result provides clear indication that total personal income growth in one county is heavily dependent on total personal income growth in neighboring counties.

The results of Model 2 indicate that knowledge becomes statistically insignificant when the interaction of knowledge and new business ventures is included as an explanatory variable in the regression model. The implication here is that it is the interaction of these two variables that impacts growth in total personal income, rather than knowledge alone. This result supports the assumption of the knowledge filter model that the production of knowledge is a necessary yet insufficient provision for yielding economic growth. It also appears that the contribution of newly created knowledge in a region to economic growth depends on the propensity of a region to create new business ventures that are adept at commercializing this newly created knowledge. The interaction of knowledge with incumbent firms suggests that the knowledge commercialized by incumbent firms has little to no impact on the growth rate of total personal income. All other variables provide the same inferences as Model 1.

The estimation and presentation of Model 3 (which includes all of the variables) provides the last important piece of additional information presented in this section of this analysis. Examination of the results obtained from the estimation of Model 3 indicate that the interaction of knowledge with new business ventures have positive and statistically significant impacts on the growth rate of total personal income. Both density and the log of total personal income have negative and statistically significant impacts on total personal income growth while knowledge, the R&D dummy, new ventures, incumbents, and the interaction of knowledge with incumbents have effects that are not statistically significantly different from zero. This set of results also provides evidence that incumbents are not a proficient mechanism for converting newly created knowledge into commercialized, economically useful knowledge. In summary, the results obtained from the estimation of a maximum likelihood SAR model provides evidence in support of both Hypotheses 2 and 3 while the evidence does not support Hypothesis 1.

5.4 Spatial Panel Results

Table 5 contains the results obtained from estimating the pooled model (Equation 6) with the inclusion of a spatially lagged dependent variable for same three equations presented in Table 4. The results associated with Model 4 show that knowledge and new business ventures are positively related to the growth rate of total personal income at the one percent level. Incumbents, density, and the log of total personal income are associated with negative and statistically significant impacts on total personal income growth, while the R&D dummy is associated with an impact that is not statistically significantly different from zero.

Model 5 again demonstrates that the interaction of knowledge with new business ventures has an impact on economic growth. Under this estimation procedure, however, knowledge remains positive and statistically significant, whereas, it became insignificant in Model 2 of Table 4 when the new venture and knowledge interaction term was introduced. Both density and the log of total personal income remain negative and statistically significant; again indicating convergence in total personal income across the period 1990 – 1999 and that density has a negative relationship to total personal income growth in our sample declining economy.

Table 5. Pooled model with spatially lagged dependent variable and no fixed effects

1990 – 2000 (panel) Ohio Counties (N = 880)	Model 4 (r^2 = 0.53)	Model 5 (r^2 = 0.54)	Model 6 (r^2 = 0.54)
Constant	0.045*** (3.813)	0.044*** (3.835)	0.046*** (3.932)
Knowledge	0.734*** (8.672)	1.242*** (5.760)	1.127*** (4.149)
Rddummy	0.003 (1.578)	0.002 (1.090)	0.002 (1.262)
NewVentures	1.601*** (4.002)		0.783 (1.470)
Incumbents	-0.320*** (-3.610)		-0.118 (-.0971)
Density	-0.001*** (-3.266)	-0.001*** (-2.504)	-0.001*** (-2.635)
LogTotInc	-0.002*** (-2.476)	-0.003*** (-2.984)	-0.003*** (-2.800)
K*NV		0.965*** (4.472)	0.667** (2.300)
K*Incumb		-2.960*** (-3.878)	-2.281** (-2.179)
Rho	0.720*** (26.039)	0.722*** (26.353)	0.720*** (25.920)

Significance: '*" at the 90% level, '**' at the 95% level, and '***' at the 99% level - t-statistics are shown in parentheses

In Model 6, knowledge and the interaction of knowledge with new business ventures have positive and statistically significant impacts on the growth rate of total personal income, while new and incumbent firms, by themselves, have influences that are not statistically significantly different from zero. Density and the log of total personal income, again, have negative and statistically significant impacts. In addition, the interaction of knowledge with incumbent firms is associated with a negative and statistically significant impact on the growth rate of total personal income. This last finding suggests that the commercialization of knowledge by incumbent firms may actually have a negative influence on total personal income growth when a more robust estimation technique is utilized.

Table 6 reports the set of estimation results of Equation 7. This set of results extends the spatial panel modeling framework to include both a spatially lagged dependent variable as well as time period effects when estimating the three equations presented above. The results associated with the estimation of Model 7 indicate that the knowledge, R&D and the new business venture variables have positive and statistically significant influences on total personal income growth. Incumbents, density, and the log level of total personal income are associated with negative and statistically significant impacts on economic growth.

Model 8 again replaces new and incumbent firms with their respective interactions with knowledge. The results of the estimation of this relationship suggest that the interaction of new firms with knowledge is positive while the interaction of knowledge with incumbent firms is negative; both of these findings are statistically significant. As well, knowledge remains positive and significant while the R&D dummy is no longer statistically significantly different from zero. Density and the log of total personal income remain negative and statistically significant, providing evidence of convergence in total personal incomes and that density in this sample has a negative relationship to total personal income growth.

Table 6. Pooled model with a spatially lagged dependent variable and time period fixed effects

1990 – 2000 (panel) Ohio Counties (N = 880)	Model 7 (r^2 = 0.55)	Model 8 (r^2 = 0.56)	Model 9 (r^2 = 0.56)
Knowledge	0.772***	1.213***	1.152***
	(9.125)	(5.579)	(4.294)
Rddummy	0.004*	0.003	0.003
	(1.904)	(1.454)	(1.531)
NewVentures	1.575***		0.580
	(3.804)		(1.081)
Incumbents	-0.276***		-0.066
	(-3.153)		(-0.551)
Density	-0.001***	-0.001***	-0.001**
	(-2.947)	(-2.148)	(-2.274)
LogTotInc	-0.002**	-0.003***	-0.003***
	(-2.522)	(-2.981)	(-2.852)
K*NV		1.008***	0.797***
		(4.640)	(2.802)
K*Incumb		-2.736***	-2.356**
		(-3.619)	(-2.297)
Rho	0.425***	0.417***	0.434***
	(10.014)	(9.730)	(10.292)

Significance: '*' at the 90% level, '**' at the 95% level, and '***' at the 99% level - t-statistics are shown in parentheses

Results obtained from the estimation of Model 9 indicate that knowledge and the interaction of knowledge with new business ventures have positive and statistically significant impacts on total personal income growth while density, the log level of total personal income, and the interaction of knowledge with incumbent firms have negative and statistically significant impacts. Once again, new and incumbent business ventures become insignificant when the interaction of knowledge with these variables were included as an explanatory variable.

Taken together, the spatial panel regression models provide considerable evidence in support of Hypotheses 2 and 3, but no support Hypothesis 1. Density appears to have a negative relationship with regard to our declining economy while the negative sign on the log level of total personal income suggests convergence has occurred in total personal incomes during the 1990's. These results provide considerable evidence in favor of the knowledge filter growth model, as they are provided by one of the most robust applicable regression models currently available.

6. Discussion

Given the similarity of approach, data, and results to the previous paper by Acs and Plummer (2005) it would be useful and instructive to expand the comparison between the results for Ohio with the previous results for Colorado in a more explicit and somewhat more detailed manner. The findings in Acs and Plummer (2005) suggested that new firms were more important in the commercialization of new knowledge than incumbents. This made some sense in an expanding high technology economy where new knowledge played an important role in the economy. In a declining state, where knowledge in large industrial research laboratories dominated the economy, we would have thought that incumbents would play a more, not less, important role in contributing to economic growth.

The coefficient on the interaction term for knowledge by high technology births was 609.23 in Colorado, significant at the 95% level, while in Ohio it was 2.578 and significant at the 99% level. While the coefficient on the interaction term for knowledge by incumbents in Colorado was negative and tiny (-0.09 at the 95% level) in Ohio it was - -1.579 and statistically insignificant. The results seem to suggest that the role of high tech births, if anything, were at least as important in Ohio, not less. Moreover, the results on the knowledge by incumbent's interaction were also similar in Ohio, although not statistically significant. These results were robust with respect to both time and alternative model specifications. How do we interpret these results given the history of incumbents and the research laboratory in Ohio?

One answer to this anomaly can be explained by the fact that Ohio has restructured away from a "rustbelt" state to a more progressive state based on knowledge creation, government services, universities and entrepreneurship. In this environment high tech startups play a more, not less important role in the economy. This restructuring in Ohio is evidenced by the fact that Columbus, Ohio is now a larger and more important city than Cleveland, Ohio in terms of economic activity. In other words, Cleveland was never able to recover from the industrial decline in heavy manufacturing. Therefore, the coefficient on the interaction term between knowledge and incumbents is both larger and more significant in Ohio than in Colorado, a state that did not have to restructure to the extent of Ohio. Ohio exhibits the same results as Colorado, in part, because the declining industry and knowledge base has never recovered yet a new knowledge base has been created where new knowledge-based high tech startups play a more important role than incumbents.

7. Conclusions

The contributions made by endogenous growth theorists have done much to improve the understanding of the complex process of economic growth to be sure. However, the basic model does not sufficiently explain the transition of newly created knowledge to commercialized, or rather, economically useful knowledge at the micro-level. Furthermore, the explanation of the diffusion of outputs from aggregate knowledge investments, in the form of "knowledge spillovers," is inadequate as the assumptions associated with these types of growth models lack both theoretical and intuitive appeal. As well, and perhaps more importantly, they lack empirical backing. It is one thing for technological opportunities to exist, but an entirely different thing for them to be discovered, exploited and commercialized (Shane and Echkardt, 2003).

The purpose of this paper was to test the validity and generalizability of the theoretical knowledge filter model by applying the model to previously untested regions of the U.S. economy, i.e. the regions in economic decline. To make this assessment, a dataset reflecting a "typical" declining economy was identified and analyzed by the utilization of recent developments in the spatial econometric literature, most notably the extension of spatial econometric models to spatial panel datasets. The estimation procedures facilitate inferences regarding the specific hypotheses that are specifically derived from the theoretical model. The emphasis of this paper was placed on determining the validity and generalizability of the knowledge filter model to economies suffering from recent economic decline.

The results of our analysis have provided evidence in support of the theoretical model with regard to two of our three specific hypotheses. Specifically, the contribution of knowledge in a region to economic growth depends on the propensity of a region to create new business ventures and that the contribution of newly created knowledge to economic growth in a region depends more strongly on newly created business ventures than on the absorptive capacity of existing incumbent firms. The evidence has also shown that knowledge is, indeed, a necessary condition, yet, by itself an insufficient explanation of economic growth.

We did not, however, find evidence to support our hypothesis that the contribution of newly created knowledge in a region to economic growth depends on the absorptive capacity of incumbent firms in a region. In fact, we found that the interaction of knowledge with incumbent firms has a negative impact on economic growth, as measured by the growth rate of total personal income. This finding is consistent with that found in Acs and Plummer (2005) and, as they indicate, may be a function of the specification of the incumbent firms variable. Furthermore, this result may reflect the fact that when local operations of corporations do absorb knowledge spillovers, the contribution to growth may occur in other regions, such as the location of the corporate headquarters.

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