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Penetrating the knowledge filter in the rust belt

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Penetrating the Knowledge Filter in the Rust Belt

by

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Penetrating the Knowledge Filter in the Rust Belt

September 2007

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Abstract

A new model of economic growth introduces the knowledge filter between new knowledge and economically useful knowledge. It identifies both new ventures and 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 those 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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Endogenous Growth

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I. 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 (2004, 2005) 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 concerted *actions* and the bearing of relevant costs by new and existing

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).

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 (Acs et al, 2004) in the context of *declining* regional economies (Carlsson, et al, 2007). 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. A rustbelt city is one that experiences population loss, rising crime rates, loss of union jobs, particularly in manufacturing, white flight to the suburbs, ... (<http://gangresearch.net/Archives/hagedorn/rustbelt.html>).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 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 Acs et al's (2004) knowledge filter growth model and develops the hypotheses to be tested. Section 4 describes the research design and

⁴ The manufacturing belt, sometimes nicknamed the rustbelt, is an area in parts of the Midwest and the Mid-atlantic regions of the United States. Other countries, especially the United Kingdom and Western Europe have very similar regions that were based on heavy manufacturing that declined during the 1980s and 1990s.

section 5 reports the results of our analysis. Finally, section 6 will provide some conclusions.

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 across 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

As enumerated by Acs et al (2004), the basic endogenous growth model relies 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 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

According to Acs et al (2004), 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

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).

necessary? The answer is that the assumption of firm specificity is necessary to justify that only a *portion* 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 (Acs et al, 2004). 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”

As Acs et al (2004) contend, the basic endogenous growth model does 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

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 be no incentive to invest in the production of knowledge resulting in no, or at least less, growth.

assumptions lacks both theoretical and intuitive appeal as well as empirical backing. Indeed, it is one thing for technological opportunities to exist, but an entirely different matter for them to be discovered, exploited and commercialized (Acs and Varga, 2002).⁸ Given this premise, Acs et al (2004) develop a model that extends the basic endogenous growth model and incorporates the mechanisms by which knowledge is made to contribute to growth.

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, Acs et al (2004) contend 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

⁸ Acs and Varga 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.

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, 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^{cl} , and the second involves the entrepreneurial startup of new (Schumpeterian) firms, K^{cSch} ,

$$K^c = K^{cl} + K^{cSch}. \quad (1)$$

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),

$$K^c = (\theta + \lambda)K, \quad 0 \leq \lambda + \theta < 1. \quad (2)$$

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^{cl} , 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 $k_{i,t}^I$,

$$k_{i,t}^I = f\left(\int_{t=0}^t k_{i,t}^I dt, K\right), \quad \sum_i^n k_{i,t}^I = K_t^I, \quad K_t^{cl} = \theta K, \quad \theta < 1 \quad (3)$$

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,

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

Thus, we contend,

Hypothesis 2: 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 (Audretsch, 1995, Ch. 3). In particular, there are strong disincentives

⁹ Schumpeter (1911).

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 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 Acs et al (2004) 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

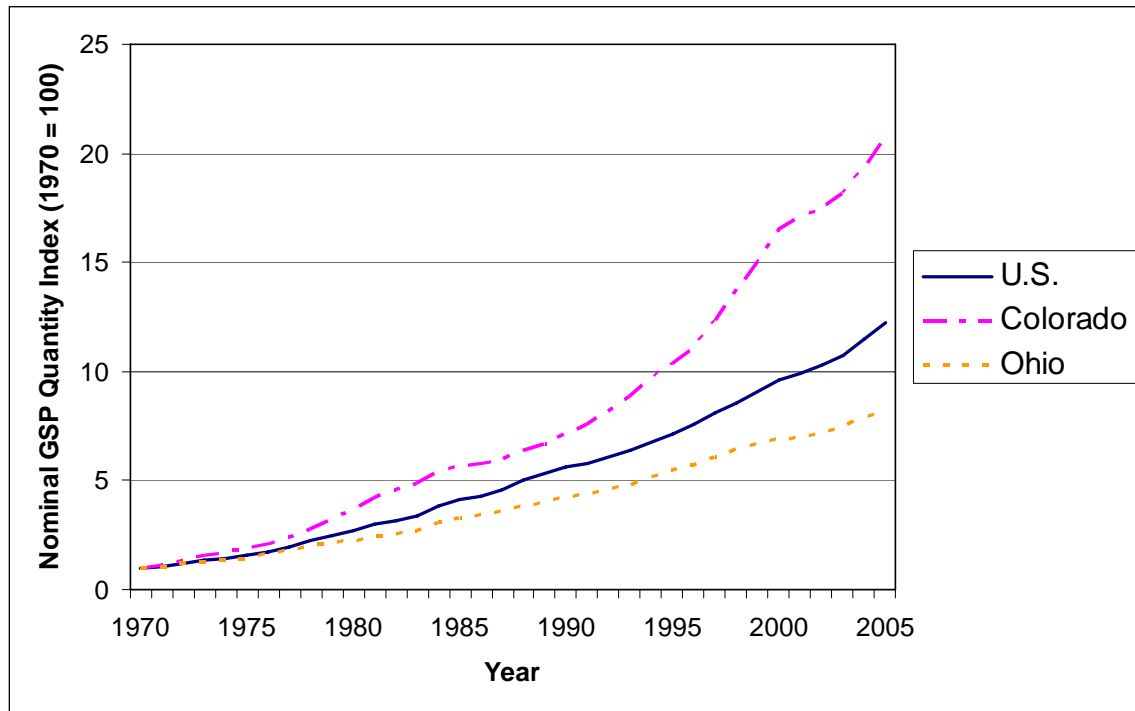
Aside from the theoretical basis discussed above, the sample of Ohio counties is based on criteria suggested by Acs and Plummer (2005) and the data are collected to afford comparability with their analysis. In particular, the sample for this study contains adequate variance in the variables in the model 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 Plummer's 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 "rustbelt" 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

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

with the United States average until 1979 and began to lag considerably thereafter. Colorado, by comparison, began to surge ahead in 1975 with a slight retraction toward the national average during the 1990 recession. After that period, Colorado surged

Figure 1. Annual Change in Nominal Gross State Product 1970-2005



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

strongly ahead of the U.S. average with a minor retraction after 2000. 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 an Ohio an appealing 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 stocks are 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 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 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. These industries are identical to those reported by Acs and Plummer (2005).

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 formation 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.

¹¹ A single-establishment birth is defined as an establishment having no payroll in the first quarter of an initial year followed by positive payroll in the first quarter of a subsequent year.

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.

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 bias in traditional regression methodologies such as OLS (Anselin, 1998; LeSage, 1997). Furthermore, heteroscedasticity 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, as demonstrated by Acs and Plummer (2005). 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, including Moran's I, as well as employ spatial regression methodologies.

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 routines to produce coefficient estimates that differ in magnitude on a scale dependent on the extent and size of the outliers.

To address any collinearity problems, we rely on 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 exist in the sample data (Elhorst, 2003, 2005).

4.4. Spatial Autoregressive Model

To test for as well as take into account the influence of spatial dependence across the observations in our sample, we estimate a spatial autoregressive (SAR) model of the following form:

$$\begin{aligned} y &= \rho W y + X\beta + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I_n) \end{aligned} \tag{5}$$

where W denotes an 88×88 spatial weights matrix, which defines the set of neighboring counties for each observation, and ρ is a scalar parameter measuring the strength of the relationship between the dependent variable, y_i , and the spatially lagged variable vector, $W y_i$. 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 weights matrices are based on (1) a first-order contiguity based specification and (2) on a sequence of 20 weights 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.¹²

4.5 Spatial Panel Data Models

We exploit the advantages of our panel data by estimating two panel data models. The first model (Equation 6) is a pooled model with the inclusion of a spatially lagged dependent variable. The second model (Equation 7) is a pooled model that includes a spatially lagged dependent variable as well as time fixed effects. The specification of the second model is based on three factors. First, random effects are inappropriate when

¹² This was accomplished using LeSage’s (CITE) “sar_g” and “model_probs” Matlab functions.

observations are based on irregular spatial units such as counties (Elhorst, 2003, 2005; Anselin, 1988). Second, the assumption of zero correlation between μ and X in the random effects model is restrictive and unlikely to hold (Elhorst, 2003 and 2005). Lastly, we exclude spatial (i.e., county) fixed effects because spatial fixed effects cannot be consistently estimated (Elhorst, 2003).¹³ In contrast, time fixed effects can be consistently estimated. The two models – with W the row standardized first order contiguity weights matrix described above – take the form,

$$\begin{aligned} y_t &= \rho W y_t + X_t \beta + \varepsilon_t \\ \varepsilon_t &\sim N(0, \sigma^2 I_n) \end{aligned} \quad (6)$$

and

$$\begin{aligned} y_t &= \rho W y_t + X_t \beta + \mu + \varepsilon_t \\ \varepsilon_t &\sim N(0, \sigma^2 I_n) \end{aligned} \quad (7)$$

The models 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). Next, given the inclusion of the spatial lag and the resulting statistical complications, we use a two stage procedure, with the intercept estimated as $\beta_1 + \mu_i$ (Anselin 1988, 181-182), to maximize the log-likelihood function (Elhorst 2003, 250) yielding maximum likelihood estimates (MLE) of the relevant parameters.¹⁴

¹³ In our panels, $T = 10$ and $N = 88$. In the spatial panel context, T is 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.

¹⁴ The models were estimated using the “sar_panel” Matlab function (Elhorst, CITE).

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

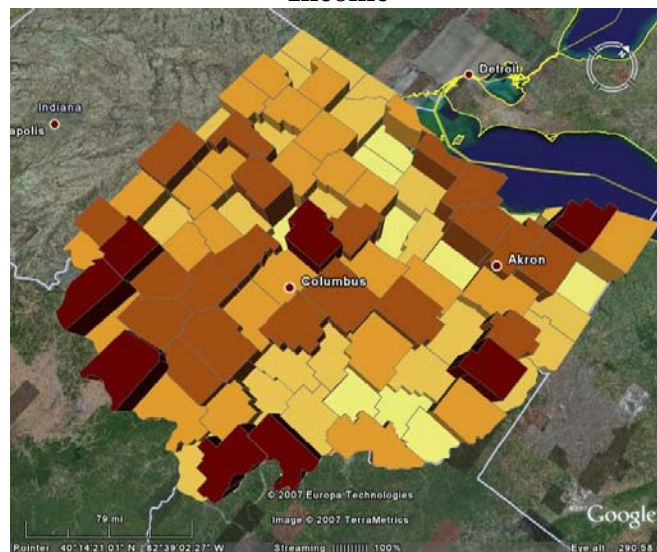
Table 1. Descriptive Statistics

Variable	Mean	STD	Min	Max
Total Personal Inc.	0.047	0.011	0.028	0.108
Density	6.545	12.524	0.362	79.132
LogTotInc	14.071	1.103	12.029	17.424
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. The mean density was 6.55 with a standard deviation of 12.52, indicating considerable variability in the density of a given county. 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. The average number of patents (knowledge) was 8 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 with a range of 0 to 6 per 1,000 establishments with the maximum value again occurring 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.

Figure 2. Spatial Distribution of the Average Annual Growth Rate of Total Personal Income



A map of the average annual change in total personal income is shown in Figure 2, where clear patterns of spatial clustering illustrate spatial dependence. In Figure 2, neighboring counties tend to exhibit similar average annual growth rates, reflected in this Figure by clusters of counties with similar growth rates. Further 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 test statistic associated with this value is 6.12, which is clearly large than the 95% critical value of 1.96, yielding a marginal probability level of 0.000. This evidence provides a clear indication of statistically significant spatial dependence.

Table 2 contains 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 Spatial autoregressive results

We find that heteroskedasticity, outliers, and collinearity are not influential factors in the data and, therefore, we do not report the Bayesian heteroscedastic linear SAR results or the complete set of alternative specifications of the regression models, based on alternative permutations of the explanatory variable matrix. We do, however, include a few alternative model specifications in order to illustrate a few important points. Lastly, OLS results are not presented as the existence of spatial dependence has been demonstrated both above, as well as below in Tables 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, hence, OLS estimates are not to be relied upon as spatial dependence has been shown to exist in the sample data (LeSage, 1997).

The model comparison techniques utilized to ascertain the most appropriate specification of the spatial weights matrix indicated that the first order contiguity weights matrix was associated with the largest posterior model probability and, hence, this specification of the spatial weights matrix was utilized in every instance where a W was required.

Three sets of results, obtained from estimation of the Maximum likelihood SAR regression model, are contained in Table 3. Column 2 of Table 3 contains a model (Eq. 1) including all of the variables discussed in Section 4.1. Column 3 contains a model (Eq. 2) that includes an additional variable, the interaction between knowledge and new high technology business ventures, while omitting the incumbent firms variable. Column 4 contains a model (Eq. 3) that includes all of the variables discussed in Section 4.1 as well as two interaction terms, the interaction between knowledge and new ventures as well as the interaction between knowledge and incumbent firms.

Table 3. Maximum likelihood spatial autoregressive results

Variables	Eq1 (0.53)	Eq2 (0.59)	Eq3 (0.60)
Constant	0.064***	0.056***	0.057***
Knowledge	0.525***	-0.172	0.330
Rddummy	0.002	0.000	0.001
NewVentures	6.233***	1.717	1.872
Incumbents	-0.274**		-0.025
Density	-0.001**	-0.0011**	0.001***
LogTotInc	-0.004***	-0.003**	-0.003***
K*NV		2.911***	2.573***
K*Incumb			-1.586
Rho	0.618***	0.603***	0.622***

Significance: ‘*’ at the 90% level, ‘**’ at the 95% level, and ‘***’ at the 99% level - R-squares are in parentheses

Examination of the results obtained from estimation of equation 1 indicate that knowledge and new high technology business ventures have positive and statistically significant impacts on the average annual growth rate of total personal income at the 99 percent level. Density and the log of total personal income have negative and statistically significant impacts on the growth rate of total personal income at the 95 and 99 percent

levels, respectively. Incumbent firms are associated with a negative and statistically significant parameter estimate at the 95 percent confidence level.

Equation 2 provides important additional information when presented in tandem with equation 1. The results associated with the estimation of equation 2 indicate that both knowledge and new business ventures have affects on the growth rate of total personal income that are not statistically significantly different from zero 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 these two variables individually. This result provide considerable evidence in support of the capability of the knowledge filter model of growth to better explain economic growth, for in this model knowledge production in a necessary yet insufficient provision for yielding economic growth. Rather, in this model it is the interaction of knowledge with a mechanism capable of penetrating the considerable barriers to commercialization or the “knowledge filter” that yields economic growth. In the case of equation 2, the interaction of knowledge with new business ventures is shown to positively impact economic growth, while the two affects individually are not. This finding provides considerable evidence in support of hypothesis two, laid out in Section 3.4, where it is hypothesized 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 estimation and presentation of equation 3 provides the last important piece of additional information in this Section of the paper with regard to the purposes of this analysis. Examination of the results obtained from the estimation of equation 3 indicate that both density and the interaction of knowledge with new business ventures have

positive and statistically significant impacts on the growth rate of total personal income at the 99 percent level. The log of the level of total personal income has a negative and statistically significant impact on total personal income growth while knowledge, new ventures, incumbents, and the interaction of knowledge with incumbents have affects that are not statistically significantly different from zero. This set of results provides evidence that incumbents are not a proficient mechanism for converting newly created knowledge into commercialized, economically useful knowledge, thus hypothesis 1 is not supported.

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.

5.3 Spatial Panel Results

Two spatial panel data regression models are utilized in this section of the paper in an effort to exploit the advantageous properties (discussed above) inherent in these types of regression methodologies. The first model involves the estimation of a traditional pooled model with the addition of a spatially lagged dependent variable. The second model involves the estimation of a pooled model with the addition of both a spatially lagged dependent variable as well as time fixed effects.

Table 4 contains the estimation results obtained from estimating a pooled model with the inclusion of a spatially lagged dependent variable for same three equations presented in Table 3. The results associated with equation 1 show that knowledge and new business ventures are positively related to the growth rate of total personal income at the 99 percent level. Incumbents, density, and the log of the level 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.

Estimation of equation 2 again demonstrates that the interaction of knowledge with new business ventures has an impact on economic growth that trumps the impact of new business ventures alone. In this estimation procedure, however, knowledge remains positive and statistically significant, whereas, it became insignificant when this interaction term was introduced in section 5.2. Both density and the log level of total personal income remain negative and statistically significant.

Table 4. Pooled model with spatially lagged dependent variable and no fixed effects

Variables	Eq1 (0.53)	Eq2 (0.53)	Eq3 (0.54)
Constant	0.045***	0.046***	0.046***
Knowledge	0.734***	0.550***	1.127***
Rddummy	0.003	0.002	0.002
NewVentures	1.601***	0.672	0.783
Incumbents	-0.320***		-0.118
Density	-0.001***	-0.001***	-0.001***
LogTotInc	-0.002**	-0.003***	-0.003***
K*NV		0.705***	0.667**
K*Incumb			-2.281**
Rho	0.720***	0.722***	0.720***

Significance: ‘*’ at the 90% level, ‘**’ at the 95% level, and ‘***’ at the 99% level - R-squares are in parentheses

In equation 3, 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 density and the log of total personal income 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.

Table 5 contains the last set of estimation results contained in this paper. This set of results extends the spatial panel modeling framework to include both a spatially lagged dependent variable as well as time period effects in the estimation of the three equations

presented above. The results associated with the estimation of equation 1 indicate that the R&D and the new business venture variables have positive and statistically significant affects on economic growth. Incumbents, density, and the log level of total personal income are associated with negative and statistically significant impacts on economic growth.

Equation 2 again introduces the interaction of knowledge with new business ventures into the regression equation yielding the same type of results as above. Here, one can see that the impact of new ventures, alone, becomes insignificant once the interaction term involving this variable with knowledge is introduced.

Table 5. Pooled model with a spatially lagged dependent variable and time period fixed effects

Variables	Eq1 (0.55)	Eq2 (0.55)	Eq3 (0.56)
Knowledge	0.772***	0.553***	1.152***
Rddummy	0.004*	0.003	0.003
NewVentures	1.575***	0.573	0.580
Incumbents	-0.276***		-0.066
Density	-0.001***	-0.001***	-0.001**
LogTotInc	-0.002**	-0.003***	-0.003***
K*NV		0.826***	0.797***
K*Incumb			-2.356**
Rho	0.425***	0.412***	0.434***

Significance: ‘*’ at the 90% level, ‘**’ at the 95% level, and ‘***’ at the 99% level - R-squares are in parentheses

As in Table 4, knowledge remains positive and statistically significant under the spatial panel-modeling framework regardless of the inclusion of time fixed effects. Density and the log level of total personal income are again associated with negative and statistically significant impacts on the growth rate of total personal income while R&D became insignificant.

Results obtained from the estimation of equation 3 indicate that knowledge and the interaction of knowledge with new business ventures have positive and statistically

significant impacts on economic 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 business ventures became insignificant when the interaction of knowledge with new business ventures was included as an explanatory variable.

Taken together the spatial panel regression models provide evidence in support of hypotheses 2 and 3. Here again, the evidence runs counter to hypothesis 1 as the evidence provided by the regression results suggests an impact counter to the impact that was suspected.

6 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.

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.

In general, the results of our analysis have provided support for the knowledge filter model of endogenous growth (Acs et al 2004) and the knowledge spillover theory of entrepreneurship (Acs et al, 2005). We have demonstrated that this model pertains not only to expanding economies but to declining economies as well (Carlsson, et al, 2007). Therefore, previous empirical support for the model can not as easily be attributed to nuances in the specific dataset as they have held up with regard to a dataset representing a declining economy as well as to estimation procedures capable of incorporating both spatial and temporal effects.

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