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Penetrating the "Knowledge Filter" in Regional Economies

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ABSTRACT
New knowledge in the form of products, processes and organizations leads to opportunities that can be exploited commercially. However, converting new ideas into economic growth requires turning new knowledge into economic knowledge that constitutes a commercial opportunity. Acs, Audretsch, Braunerhjelm, and Carlsson (2003) develop a model that introduces a "knowledge filter" between new knowledge and economic knowledge and identifies both new ventures and incumbent firms as the mechanism that reduces the knowledge filter and increases regional growth. This paper tests the hypotheses that new venture creation is a better mechanism than the absorptive capacity of incumbent firms for converting new knowledge into economic knowledge. Our results support the contention that new venture creation is a superior method of penetrating the regional "knowledge filer" than incumbent firms.

JEL: M13, O10, O18, O30, L10
Keywords: Regional growth, knowledge, new venture creation, entrepreneurship

INTRODUCTION*

New (endogenous) growth theory has allowed for impressive advances in the understanding and modeling of economic growth. Unlike neoclassical growth models (Solow 1956, 1957), which emphasize the link between capital, labor and economic performance, new growth theory models highlight the role of knowledge and its contribution to increases in productivity output and efficiency. As such, knowledge spillovers are considered a key element in new growth theory models. These knowledge spillovers – the transfer of knowledge from industry or firm *i* to industry or firm *j* – represent key sources of opportunities for firms and industries to enhance process efficiency, make product improvements, and develop any number of technological and organizational innovations (Romer, 1986, 1990).

Given their purported importance to understanding the sources of economic growth, knowledge spillovers have received considerable treatment in the economic and management literatures in both empirical and theoretical studies (e.g., Griliches, 1992). Early new growth theory models treated knowledge as a public good assuming (1) that the widespread use of the same knowledge does not diminish its value to individual users (i.e., non-rival) and (2) that no one can be prevented from using it (i.e., non-excludable). These assumptions eased the conceptualizing of the early new growth theory models, but later efforts amended the assumptions to treat knowledge as non-rival, yet – in light of intellectual property rights – partially excludable. However, new growth theory models continue to assume that spillovers are

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virtually automatic, costless, and unconstrained by spatial factors such as geographic distances (Acs, Audretsch, Braunerhjelm, and Carlsson, 2003).

Empirical evidence contradicts these assumptions suggesting that knowledge spillovers are subject to legal, geographic, and cost constraints (Anselin, Varga, and Acs, 1997, 2000, Cohen, Nelson and Walsh, 2000, Jaffe, 1989, Jaffe, Tratjenberg, and Henderson, 1993). In light of this and other evidence, Acs, et al. (2003) proposes a new growth theory model that incorporates this empirical evidence and specifies a mechanism by which spillovers occur. Specifically, Acs et al. (2003) proposes that knowledge spillovers result from either (a) the active incorporation of knowledge into the existing operations of incumbent firms or (b) the founding of new ventures established specifically to exploit such knowledge. And, because new firms – despite their liabilities – tend to introduce the truly novel and unique advances in products and processes, it is entrepreneurs and the firms they found that allow spillovers to make their greatest economic contribution.

In this paper, we test two hypotheses that emerge from the AABC model. First, we test the hypothesis that knowledge depends on new venture creation and incumbents, respectively, to contribute to economic growth. Second, we test the hypothesis that, of the two, new ventures matter more than incumbent firms in allowing knowledge spillovers to contribute to economic growth. In doing so, this paper applies a spatial econometric method designed to accommodate statistical problems induced by geographic effects and dependence. The next section develops and details the hypotheses that will be tested followed by sections covering, respectively, the research design, the results, and some discussion. The paper concludes with some brief remarks.

THEORY DEVELOPMENT[1]

What are the key drivers of economic growth and how should they be measured? These questions have been central issues in the empirical growth literature for some decades. The neoclassical models (Solow 1956, 1957), as mentioned, emphasize the importance of two inputs in production: capital and labor. However, the predictions of growth generated from these models typically fall short of the actual growth observed. This difference between predicted and observed growth is commonly referred to as the "Solow residual" or "technical residual." This residual is often credited to differences in technology and knowledge used in production – variables not captured in the neoclassical model. By incorporating – or making endogenous – knowledge as a variable, new growth theory models account for a greater portion of the residual than neoclassical models. And, most interestingly, the knowledge produced by a profit-maximizing firm has the duel effect of (1) making the firm itself more efficient and productive and (2) spilling over into the economy to cause changes in production methods or technologies (i.e., a shift in production functions) in other firms or industries. This duel effect of knowledge enables economic growth that exceeds the combined value of any productive inputs such as capital or labor (Acs, et al. 2003).

To obtain this result, new growth theory models make several assumptions regarding technology, firms, knowledge, and geography. Two of these assumptions are particularly salient: First, new growth theory assumes firms employ firm-specific knowledge in the production of goods and that this knowledge does not depreciate in value with use over time. But, as Acs et al. (2003) point out, this assumption is at odds with new growth theory's further premise that firms are operating in competitive markets as price-takers, earning zero profits, and free of competitive entry. Under such conceptual conditions, firms employ the same technology or knowledge in

[1] What follows is drawn chiefly from Acs, Audretsch, Braunerhjelm, and Carlsson (2003).

production to produce a largely homogenous set of products all suggesting that spillovers would involve 100% of the produced knowledge. Therefore, *firm-specific* knowledge is inconsistent with the assumptions of competitive markets since it implies some monopoly control over such knowledge.

Second, new growth theory models assume that knowledge spillovers occur automatically, without cost, and with few or no constraints. However, it is shown that knowledge spillovers are constrained in a number of important ways. One, spillovers are constrained by the relatedness of practices, methods and technologies between the firm or industry generating spillovers and those receiving them (Acs, 2002, Jaffe, 1989). Two, knowledge spillovers are constrained by the effectiveness of legal institutions such as protection of intellectual property (e.g., Cohen, Nelson, and Walsh, 2002). Three, knowledge spillovers are constrained by geographic factors that limit the economic impact of spillovers to a range of 50 to 75 miles from where the knowledge was first created (Anselin, et al., 1997, 2000; Keller, 2002). Thus, it seems unsound to assume spillovers are automatic and costless.

That new growth theory models are built on perhaps flawed assumptions may explain why they receive mixed empirical support thus suggesting new growth theory models are missing a crucial factor that will afford greater accuracy in describing and predicting economic growth. And, in light of the evidence, it appears more correct to assume knowledge spillovers are costly, geographically constrained and not automatic and, in doing so, suggests that specifying *how* knowledge spillovers occur and contribute to economic growth is a missing component in most new growth theory modeling (Acs, et al. 2003). In this regard, the AABC new growth model includes new ventures and incumbent firms as the mechanism by which knowledge spillovers occur and contribute to economic growth.

Acs, et al. (2003) conceptualizes the combination of factors preventing or constraining spillovers as a *knowledge filter* – a semi-permeable barrier limiting the efficient conversion of new knowledge into economic knowledge. As such, the model takes the stock of new knowledge as given and assumes, as Arrow (1962) suggested, that not all of the knowledge is economically useful. Indeed, portions of this stock of knowledge must be transformed into useful, firm-specific knowledge through considerable effort and at some cost. Therefore, the knowledge filter must be penetrated for knowledge to be appropriated, packaged, modified, and enhanced for it to ultimately contribute to economic growth. And, those willing and able to penetrate the filter to enable knowledge spillovers are (a) incumbent firms and (b) new ventures. On the one hand, incumbent firms endowed with the capacity to recognize, evaluate, absorb, and apply to commercial ends knowledge from external sources (Cohen and Levinthal, 1990) are partly responsible for enabling spillovers. On the other, because the arbitraging of knowledge resources is a particular specialty of alert and motivated entrepreneurs (Kirzner, 1979, 1997), new ventures founded to exploit such knowledge are responsible for the balance of the spillovers. In either case, these agents actively penetrate the knowledge filter and incur the cost of doing so. Thus, the AABC model specifies that spillovers occur when the knowledge filter is penetrated and the stock of knowledge (K) is transformed into economically useful or productive knowledge (K^c) either by incumbent firms (θ) who absorb knowledge spillovers to increase productive efficiency or by new ventures (λ) founded to exploit such knowledge as a profitable opportunity. Thus,

$$K^c = (\theta + \lambda)K \qquad 0 \geq (\theta + \lambda) \geq 1 \qquad (1)$$

Acs, et al. (2003) also alters the assumption that knowledge is uniformly distributed across space. Instead, it seems likely that the taking advantage of knowledge spillovers requires transmitter-receiver proximity and face-to-face contact (Howells, 2002) and may explain, in part, why spillovers appear constrained to a range of 50 to 75 miles from where the knowledge was produced (Anselin, et al. 1997, 2000). In any event, knowledge tends to be concentrated in geographic pockets with some regions endowed with more and better quality stocks of knowledge than others. As a result, Acs, et al. (2003) – assuming that inter-regional spillovers are limited, if not nonexistent – suggests that only those incumbent firms and new ventures located inside the region[2] of knowledge spillover transform knowledge (K) into economically useful knowledge (K^c). Thus,

Hypothesis 1a: The contribution of knowledge to economic growth depends on new ventures located within the knowledge spillover region.

Hypothesis 1b: The contribution of knowledge to economic growth depends on incumbent firms located within the knowledge spillover region.

Here we depart somewhat from Acs, et al. (2003) to consider the relative importance of incumbents and new firms in transforming knowledge and its contribution to economic growth. In other words, which spillover mechanism – new ventures or incumbents – allows for a greater contribution of knowledge to economic growth? The answer lies, in part, in understanding the risks-bearing propensities, incentives, and path-dependencies of the two.

Consider first incumbent firms. The ability of incumbents to absorb knowledge spillovers at any given point depends on the knowledge accumulated in prior periods and, as a

[2] While it may seem counterintuitive that knowledge would be geographically constrained given the range of information and communication technologies, it is argued elsewhere that – while these technologies certainly contribute to the transmission of *information* – they are no substitute for physical proximity in the transfer of (particularly tacit) *knowledge* (Learner and Storper, 2001).

result, the absorption, integration, and transformation of knowledge into useful knowledge is a path dependent process (Cohen and Levithanl, 1990). And, while increased absorptive capacity generally benefits the incumbent's performance and ability to deploy innovative products and processes, this benefit is limited by competing incentives within the firm. Christensen (1997), for example, argues that increased investments in R&D and elsewhere coupled with the need to meet established growth projections tend to make incumbents wary of doing anything that may reduce the usefulness or value of existing knowledge, capabilities, or product lines. Similarly, Aldrich and Auster (1990) make the simpler argument that the larger and older the firm, the less receptive to change the organization becomes. As a result, incumbents have an incentive to develop and introduce less-risky, incremental (evolutionary) innovations into the market (Christensen, 1997). In fact, the more committed the incumbent becomes to existing products and capabilities, the less able it is to see the profit potential of externally created and available knowledge. As a result, a "disabling factor that afflicts established firms as they work to maintain their growth rate is that the larger and more successful they become, the more difficult it is to muster the rational for entering an emerging market in its early states" (Christensen 1997:132). In sum, the combination of these effects may (1) lead incumbents to apply absorbed knowledge to the development of incremental, less economically important, innovations or, worse, (2) render incumbents unable, if not unwilling, to absorb and transform knowledge spillovers even when the knowledge is readily available.

In contrast to incumbent firms, new ventures – needing justification to bear the risk, uncertainty, "liabilities of newness" and "liabilities of smallness" (Stinchcombe, 1965) of the start-up – tend to develop, use, and introduce radical, market-making products that give the firm a fighting chance against incumbents (Casson, 2002). Thus, while new firms are not subject to the path dependencies in their transformation of knowledge to useful knowledge, they seek to overcome their inefficiencies, inexperience, and resource shortages by competing through technological innovation in the Schumpeterian manner of creative destruction (Acs, et al. 2003). As a result, when new ventures do survive, succeed, and grow, the discontinuous (radical) innovations they tend to introduce to the market contribute more strongly to economic growth. Therefore,

> *Hypothesis 2: The effect of the knowledge spillovers on economic growth depends more strongly on the rate of new firm births than on the absorptive capacity of incumbent firms.*

To be clear, Hypothesis 2 is not a question of whether incumbent firms or new ventures are more innovative, but rather – of the two – which allows knowledge spillovers to contribute to economic growth more strongly. With that said, this hypothesis does build, in part, on the debate of who innovates more – incumbent firms or new ventures. Nelson (1992), for example, has suggested that the so-called Schumpeterian Hypothesis – that research and development activities are principally the domain of large industrial firms – is in fact a distortion of Schumpeter's arguments. Instead, Nelson argues, Schumpeter simply suggested that large firms are particularly adept and skilled at the administration and performance of (routinized) R&D, but not exclusively the performers of it. This reflects, in part, Winter's (1984) suggestion that innovation occurs in one of two technological regimes: (a) the entrepreneurial regime that favors innovative entry, but not the innovative activity of established firms, and (b) the routinized regime where the conditions are reversed. Acs and Audretsch (1988) supports Winter's notion of two technological regimes demonstrating in some industries, innovative activity is dominated by small, new firms and, in others, by large, incumbent firms. Since it can be established that innovative activity is the purview of both new and incumbent firms, it seems logical as a next step to assess which of the two allows knowledge to contribute more strongly to growth.

RESEARCH DESIGN

The selection of the study sample is based on three criteria. First, in light of the hypotheses and supporting assumptions, it is appropriate to conduct the analysis with a within-country sample of economic regions to avoid some of the problems of heterogeneity and limit the need for control variables. Second, with the assumption that knowledge spillovers are geographically bounded (e.g., Anselin, et al., 2000), each observation should comprise a large practicable geographic area in order to statistically represent a region of knowledge spillovers. Third, the regions in the sample must represent adequate variance in the key variables of economic growth, entrepreneurship, and knowledge spillovers for proper estimation. For these purposes, the counties in the state of Colorado are well suited as the study's sample.

Colorado is a large state (103,718 square miles) comprised of 63 counties during the study period (in 2002, Broomfield became the 64th county in the state) with an average size of approximately 1,600 square miles and considerable variation in county incomes, firm births, and innovative activity. In addition, we collected annual observations of relevant variables from each county over the period 1990 to 2000 yielding a large initial number of observations. In using the spatial econometric method for this study, we averaged the annual observations for each county leaving a final sample size of 63. The sources of the data are (1) the County Business Patterns database available from the US Census Bureau, (2) US Patent and Trademark

Office, (3) Colorado Economic and Demographic Information System, (4) the US Bureau of Economic Analysis, and (5) the National Science Foundation.

Variables and Measurement

Personal Income Growth: Using data available from the Bureau of Economic Analysis, we define the dependent variable, GROWTOT, as the annual change in personal income [(Personal income$_{(t)}$ – Personal income$_{(t-1)}$) / Personal income$_{(t-1)}$] averaged over the period 1990 to 2000.

Knowledge Spillovers (K): There are no direct measures of knowledge spillovers as they are difficult to observe. However, it follows that in regions with a larger stock of knowledge, knowledge spillovers are more prevalent. Thus, KNOWLEDGE – defined as the number of patents granted in each county divided by the number of establishments (for standardization) and averaged over the period 1990 to 2000 – will proxy for knowledge spillovers. Not surprisingly, an analysis of the variable KNOWLEDGE revealed that Boulder is a significant outlier since the county is home to the main campus of the University of Colorado, the laboratories of the National Oceanic and Atmospheric Administration (NOAA) and the National Institute of Standards and Technology (NIST), the National Center for Atmospheric Research, and many high technology firms. As a result, we control for Boulder's outlier effect by dummy coding for the county with the variable BOULDDUMM.

Additionally, since the number of patents granted can also indicate the level of R&D intensity in the county, it is important that an indicator of research and development effort be included as a control. Ideally, an indicator of all R&D expenditures in the county for the study period should be used, but this data was not found at the county level. Thus, we employ a cruder method by dummy coding for each county with R&D facilities that received some level of federal research funds during the period 1990 to 2000. This is the variable RDDUMM.

New (High Technology) Venture Formation (λ): The number of single-establishment births in each county – broken out by Standard Industrial Classification (SIC) code for 1990-1996) and North American Industrial Classification System (NAICS) code for 1998-2000 – was provided by the US Bureau of the Census. The Census defines an "establishment" as a single physical location where business is conducted or where services or industrial operations are performed, a "single-establishment" as a firm or enterprise with only one location, and an "establishment birth" – for purposes of this study – as one having no payroll in the first quarter of the initial year and positive payroll in the first quarter of the subsequent year. To isolate those establishments likely to make use of the available stock of knowledge in a county, the variable HTSBIRTHS represent "high technology" single establishment births divided by the total number of establishments in the county and averaged over 1990 to 2000. For this variable, "high technology" industries are defined following the criteria per Varga (1998). Varga combined three criteria to define high technology industries: (1) an above average R&D to industry sales ratio at the 3 digit SIC code (Acs, 1996, Acs, Fitzroy, and Smith, 1998), (2) an above average percentage of engineers, engineering technicians, scientists and mathematicians of total industry occupations (Glasmeier, Markusen, and Hall, 1983), and (3) the total number of innovations per 1,000 employees (Acs and Audretsch, 1988). The resulting set of SIC codes and mapped NAICS codes are displayed in the appendix.

Incumbents (θ): Missing from data collected from the Census (County Business Patterns database) is any indication of establishment age for use in defining incumbents. We therefore assume that an establishment's number of employees is positively correlated with the establishment's age and its stock of available resources and define INCUMBENTS as an establishment with more than 100 employees, divided by the total number of establishments in the county for standardization, and averaged over the period 1990 to 2000. Defining incumbents in this manner helps capture the organization's absorptive capacity since this capability is a function of the combined absorptive capacity of individuals and the available of resources for learning and R&D (Cohen and Levinthal, 1990).

Agglomeration: The geographic crowding of people and businesses can itself contribute to economic growth by reducing the costs of economic transactions and increasing the availability of resources including capital and labor (Armington and Acs, 2000). Therefore, we include the measure DENSITY, defined as the total number of establishments in each county divided by square miles and averaged for the period 1990 to 2000. Furthermore, since the county of Denver represents a considerable outlier of this variable, we include a dummy variable, DENDUMM, to account for this county's outlier influence.

Total Income: The growth convergence hypothesis in economics suggests that as the wealth and size of an economy expands, the growth of that economy tends to slow and, as such, some measure of the economy's size and wealth should be included as a control variable (Ray, 1998, Durlauf, 2001). Therefore, the variable LOGINCTOT is defined as the natural log of the total personal income of each county averaged over the period 1990 to 2000.

Model Specification and Estimation

Because the final sample for this study is the 63 contiguous counties of the state of Colorado, we employ a spatial econometric method that allows for the control of spatial correlation in the observations. Specifically, we suspect our models will be spatially autoregressive since the growth in personal incomes in adjacent counties is likely to be similar. In fact, the Moran's I spatial correlation statistic for the dependent variable indicates personal income growth is positively clustered such that, on average, when one county's income growth is high, the average growth in the counties sharing its borders is also high (Moran's I = 0.29, pseudo-p < 0.01). Analyzing the location of this clustering was the logical next step.

A local indicator of spatial autocorrelation or LISA map (Figure 1) shows the location of two significant clusters of personal income growth rates driving the positive clustering indicated by the Moran's I test. First, the cluster of counties along the eastern borders of Colorado feature a "low-low" pattern where the growth in one county is matched by similar low growth in its neighbors. Second, the set of counties highlighted in the center of the state show a "high-high" cluster pattern. And as expected, there were no significant indications of either a "low-high" or a "high-low" cluster pattern representing negative autocorrelation not indicated by the Moran's I test. It should be noted that the significance test for both the Moran's I and the LISA map is based on simulation, exploratory in nature, and intended to aid in the model specification.

Insert FIGURE 1 about here

Descriptive statistics shown in Table 1 indicate that the average growth in county personal incomes for the study period was approximately 7% with a low of -0.1% in San Juan and a high of 15% in Douglas County. The average number of patents per 1,000 establishments granted in each county ranged from zero in six (particularly rural) counties to 30 per 1,000 establishments in Boulder County. Also, the average of 4 high technology births for every 1,000 establishments (with a range of zero to 20 per 1,000 establishments) in comparison to an average of 10 incumbents per 1,000 establishments (with a range of zero to 80 incumbents per 1,000 establishments) makes for an average incumbents-to-births ratio of 2.5 to 1. Finally, it is worth noting that the density of establishments ranges from 3 per square mile in rural Kiowa County along the state's Western border and 131.8 establishments per square mile in Denver.

Highlighting some of the correlations reported in Table 2, it is noticeable that all of the independent variables are positively correlated – to varying degrees – with the dependent variable, GROWTOT. In particular, the log of total incomes (0.38), the number of patents per establishment (0.37), the number of high technology births (0.21), and the number of incumbents (0.26) show relatively large and positive correlations with personal income growth. Also, the Denver dummy variable (DENDUMM) is highly correlated (0.98) with the number of establishments per square mile (DENSITY) suggesting the magnitude of the county's outlier effect. Similarly, the correlation between LOGINCTOT and KNOWLEDGE (0.58) is relatively high in comparison to the other reported correlations suggesting caution in analyzing the results that follow. Finally, it is surprising how many variables are negatively correlated with the HTSBIRTHS variable, perhaps the most interesting being the negative correlation between HTSBIRTHS and the INCUMBENTS variable (-0.16) as well as LOGINCTOT (-0.18).

Insert TABLE 1 about here

Insert TABLE 2 about here

Armed with this information, we first estimated each model using ordinary least squares (OLS) regression with specification tests for both spatial autocorrelation and spatial error. As suspected, we determined that spatial lag estimation was most appropriate given the larger coefficients and smaller p-values of the robust spatial correlation (RLM-lag) test in comparison to the robust spatial error (RLM-err) test (Anselin and Bera, 1998). Subsequently, the spatial correlation (lag) estimations reported in this paper are based on the queen-criteria, first-order contiguity weights matrix. In addition to the spatial diagnostics, we tested for heteroskedasticity, multicollinearity, and the normality of the error in each regression.

RESULTS

Insert TABLE 3 about here

An initial set of equations – without control variables – were estimated and are reported in Table 3. As the Moran's I test and LISA map suggested above, the spatial autocorrelation – captured by the lag coefficient, ρ, in each equation – is positive and significant at the five percent level in all the estimations. Moreover, the magnitude of the spatial lag coefficient suggests that the relationship of economic growth in adjacent counties is not trivial. Figure 1, for example, shows that the low growth in Kit Carson (3%) was matched by similar low growth in Cheyenne (3%). Likewise, the LISA map also shows that the average income growth of 7% in Jefferson County was similar to the growth in its east and west neighbors – Denver (7%) and Clear Creek (8%).

What makes the high-high growth cluster interesting is that the foothills of the Rocky Mountains trace the western border of Jefferson County, but the cluster pattern continues through the county of Clear Creek and into the ski country of Summit County and its neighbors. Since Interstate I-70 passes through these counties, this suggests in part, that the income earned in the Denver metro area is being spent in Colorado's recreation areas and vice-versa. This is not all that surprising since, in most cases, county borders are political, not physical, boundaries meaning income earned – either by individuals or businesses – in one county has a good chance of being spent in neighboring counties. In the end, the spatial lag coefficient controls for this effect yielding more correct coefficient estimates for the remaining variables of interest.

Equation 1 includes the two knowledge variables, KNOWLEDGE and RDDUMM and indicates a positive and significant relationship between KNOWLEDGE and GROWTOT. Equation 2, adding the variables HTSBIRTHS and INCUMBENTS to the estimation, continues to show a positive and significant relationship between KNOWLEDGE and GROWTOT. Equation 3, corresponding to Hypothesis 1a, adds the interaction between KNOWLEDGE and HTSBIRTHS. In this estimation, only the spatial correlation coefficient is significant. Equation 4, corresponding to Hypothesis 1b, includes the KNOWLEDGE by INCUMBENT interaction. As with the previous estimation, only the spatial correlation coefficients are significant. Finally, equation 5, a test of Hypothesis 2, includes both the KNOWLEDGE by HTSBIRTHS interaction and the KNOWLEDGE by INCUMBENTS interaction. These results show the spatial correlation coefficient as positive and significant and the KNOWLEDGE by INCUMBENTS interaction as negative and significant.

Table 4 displays five additional model estimations with the control variables included. In estimations 6 through 10, each equation includes the variables BOULDDUMM, DENDUMM, DENSITY, and LOGINCTOT having the effect of significantly increasing the variance explained (r-squared) for each equation. As a result, the remainder of our discussion will focus on these more correctly specified equations. Equation 6 includes the controls and the variables KNOWLEDGE and RDDUMM. The positive and significant relationship between KNOWLEDGE and GROWTOT in the previous estimations is now insignificant and, instead, only LOGINCTOT is significantly related to GROWTOT. Equation 7 adds the variables HTSBIRTHS and INCUMBENTS to the estimation resulting in a positive relationship between HTSBIRTHS and GROWTOT and a positive relationship between LOGINCTOT and GROWTOT similar to equation 6. Equation 8 adds to the equation 7 variables the KNOWLEDGE by HTSBIRTHS interaction which is large and significant. Equation 9 includes the four control variables, the two knowledge variables (KNOWLEDGE and RDDUMM), INCUMBENTS and the KNOWLEDGE by INCUMBENTS interaction. Interestingly, the KNOWLEDGE variable is positive and significant as is the variable LOGINCTOT. However, the KNOWLEDGE by INCUMBENTS interaction is negative and significant. Finally, equation 10 includes the control variables, the key variables, and the two interactions similar to equation 5. These results show a highly significant relationship between LOGINCTOT and GROWTOT. More importantly, equation 10 reveals a positive KNOWLEDGE by HTSBIRTHS interaction and a significant – but negative – KNOWLEDGE by INCUMBENTS interaction.

Insert TABLE 4 about here

It should be noted that the multcollinearity condition number in the estimates for equations 6 through 10 are high, but below the cutoff of 30 in all cases except equation 10.

Examination of the data indicates this minor multicollinearity is driven by the variable LOGINCTOT, most likely as a function of its relatively high correlation with the variable KNOWLEDGE. Additional regressions (not reported here) of equations 6 through 10, dropping the variable LOGINCTOT, generally do not contradict the results in Table 4 with the exception of equation 10. In the alternative specification of equation 10 both the KNOWLEDGE by HTSBIRTHS and the KNOWLEDGE by INCUMBENTS interaction are insignificant.

Similarly, to gauge the influence of alternative weights matrices, we re-estimated equations 6 through 10 (again, the results are not reported here) first using a 50-mile distance-based weights matrix and then a 75-mile distance-based weights matrix and included the variable LOGINCTOT. These results differed little from the estimations reported in Table 4, again with the exception being equation 10. In both the 50-mile and 75-mile weighted regressions of equation 10, only the KNOWLEDGE by INCUMBENTS interaction – negative in both cases – remained significant. These alternative specifications suggest the results in equations 6 through 9 are relatively stable and robust, but urge caution in interpreting the results of equation 10 in Table 4.

DISCUSSION

Focusing on the equations in Table 4, support for Hypothesis 1a is indicated by a positive and significant KNOWLEDGE by HTSBIRTHS interaction in equation 8. Particularly interesting about these results is that the relationship between knowledge and growth is negligible when the value of HTSBIRTHS is zero. In this instance, as the birth rate of high technology ventures increases, so does the positive relationship between knowledge and growth – and quickly. The particularly large interaction coefficient implies a powerful relationship between new, high technology births and the economic growth within the county, but as causality in this relationship cannot be established additional analysis of the data is clearly warranted.

In contrast, Hypothesis 1b is not supported by the results in equation 9. In fact, the negative and significant interaction of KNOWLEDGE and INCUMBENTS was surprising since the results show a positive relationship between knowledge and growth when INCUMBENTS equals zero. However, as the value of INCUMBENTS rises, the positive relationship between knowledge and growth diminishes. This result may be due to the way the incumbents variable was operationalized. Specifically, the variable INCUMBENTS includes both single- and multi-establishments in all industries and we cannot differentiate between the economic influences of the local operations of larger corporations (e.g., IBM or Sun Microsystems) and Colorado-headquartered companies (e.g., StorageTek). It may be, for example, when the local operations of corporations do absorb knowledge spillovers, the ultimate growth contribution is not local but elsewhere, possibly in the region where the corporation is headquartered. In any event, this calls for revisiting these results with alternative specifications of the incumbent variable.

Finally, Hypothesis 2 is supported by equation 10 since the significant KNOWLEDGE by HTSBIRTHS interaction is positive while the KNOWLEDGE by INCUMBENTS interaction is negative. However, we have already qualified these results since they are not supported by alternative model specifications. Nevertheless, the results do suggest that the positive relationship between growth and high technology starts is considerable in comparison to incumbent operations. In fact, the difference in the magnitude of their respective effects the capacity of new firms to exploit new knowledge and apply it in their innovative activities far outstrips that of incumbent firms.

Such as conclusion echoes indications of the superiority in the relative quality and quantity of the innovation performed by new and small firms versus large firms. For example, research shows that small firms are 13 times more innovative per employee, twice as likely to have a patent in the top 1 percent of highest-impact patents, and more likely to have a patent cited than large firms (Baumol, 2004). Indeed, Williamson suggests that the "disabilities" suffered by large firms in the early stages of innovation leads him to hypothesize that "an efficient procedure by which to introduce new products is for the initial development and market testing to be performed by independent inventors and small firms (perhaps new entrants) in an industry, the successful development then to be acquired, possibly through licensing or merger, for subsequent marketing by a large multinational enterprise" (1975: 205-206).

There are, however, three important limitations to this study aside from the common issues of accuracy and generalizability. First, we collapsed (averaged) our original eleven period panel dataset in order to use current cross-sectional spatial econometric methods. As a result, we paid the penalty of reduced power and fidelity in our analyses. Alternative estimation methods like panel regressions would be appropriate, but the significant spatial correlation in the data directs our attention to spatial panel analysis tools now under development. These forthcoming analysis tools will allow us to revisit these data with spatial panel estimation techniques. Second, we believe our results are limited by the lack of temporal information in the data. We have, for example, no indications of the age of the incumbents or the pace at which they have grown nor do we have information on the survival and growth of the new ventures. Since these factors weigh on the absorptive capacity of both incumbents and the performance of new ventures, it would be helpful to include them in future analyses. Indeed, having information on which to define incumbents as a function of their age as opposed to their size may yield significant results in favor of Hypothesis 1b. And, finally, since our study is limited to the state of Colorado, expanding the geographic scope of study beyond the state of Colorado will enhance the power and generalizability of the results. Doing so, however, will likely demand a larger set of control variables.

CONCLUSION

This paper set out to test two hypotheses that emerged from an endogenous model of the knowledge filter featuring new ventures and incumbent firms as the critical mechanism by which knowledge spillovers occur. We have shown that the relationship between knowledge and economic growth is moderated by new ventures and that this effect is not trivial. By implication, our results support the conjecture in Acs, et al. (2003) that knowledge spillovers, new venture creation, and the interaction of the two are localized, regional phenomena. In contrast, we expected similar results regarding incumbent firms, but instead found that incumbents negatively moderate the relationship between knowledge and growth. However, we find it difficult to imagine that the knowledge spillovers absorbed by incumbent firms do not somehow, if marginally, yield some economic contribution. We have suggested one interpretation that the outcome of absorption of knowledge spillovers by incumbents ultimately contributes to growth elsewhere in other regions. And, if this is indeed the case, several fascinating implications for strategy research emerge.

For example, research may show that incumbent operations can serve as a conduit for knowledge to flow from one region to another suggesting the importance of including geographic factors in formulating corporate innovation, expansion, relocation, and merger strategies. Such a suggestion is consistent with other calls for incorporating spatial considerations in strategy research (Krugman, 1994, Porter, 1991). Similarly, if regional location shapes the flow and accessibility of knowledge, these factors may very well enhance the success and growth of new ventures. Specifically, while between region decisions may be obvious (e.g., to start a business in Boulder, Colorado instead of Pueblo, Colorado), we believe examining the within-region location decision may yield more powerful insights into the entrepreneurial and competitive nature of new venture creation. Can an entrepreneur, for example, by knowing the boundaries of the knowledge region, parlay that knowledge into some advantage to enhance the survival and growth potential into a newly created firm? If so, the implications are far reaching and the availability of spatial statistical methods is a ready compliment to theoretical research in this direction. In any event, studies assessing the role of new ventures and incumbents in economic growth will not only yield public policy insights, but will also suggest improvements and directions in strategy and entrepreneurship research.

REFERENCES

Acs, Z., Fiztroy, F., & Smith, I. (1998) “High Technology Employment and University R&D Spillovers: Evidence from US Cities.” *Economics of Innovation and New Technology,* 8: 57-78.

Acs, Z. (2002). *Innovation and the Growth of Cities*. Northampton, MA: Edward Elgar.

Asc, Z. & Audretsch, D. (1988) “Innovation in Large and Small Firms: An Empirical Analysis.” *American Economic Review,* 78: 678-690.

Acs, Z., Audretsch, D., Braunerhjelm, P., & Carlsson, B. (2003). “The Missing Link: The Knowledge Filter and Endogenous Growth.” Center for Business and Policy Studies, Stockholm, Sweden.

Aldrich, H. & Auster, E. (1990) “Even Dwarfs Started Small: Liabilities of Age and Size and Their Strategic Implications,” in L.L. Cummings (ed) *The Evolution and Adaptation of Organizations*: pp. 67-100. Greenwich: JAI Press.

Anselin, L., & Bera, A. (1998) “Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics.” In *The Handbook of Applied Economic Statistics,* eds. A. Ullah & D. Giles, 237-289. New York: Marcel Dekker.

Anselin, L., Varga, A., & Acs, Z. (1997) “Local Geographic Spillovers Between University Research and High-Technology Innovation.” *Journal of Urban Economics*, 42: 422-448.

Anselin, L., Varga, A., & Acs, Z. (2000) “Geographic and Sectoral Characteristics of Academic Knowledge Externalities.” *Papers in Regional Science,* 79 (4): 435–443.

Armington, C. & Acs, Z. (2002) “The Determinants of Regional Variation in Firm Formation.” *Regional Studies*, 36(1): 33-45.

Arrow, K. (1962) “The Economic Implications of Learning by Doing.” *Review of Economics and Statistics,* 80: 155-173.

Baumol, W. J. (2004) “Entrepreneurial Enterprises, Large Established Firms, and Other Components of the Free-Market Growth Machine.” *Small Business Economic,* 23(1): 9-21.

Casson, M. (2002) *The Entrepreneur: An Economic Theory, 2nd Ed.* Northampton, MA: Edward Elgar.

Christensen, C. (1997) *The Innovator’s Dilemma*. Boston: Harvard Business School Press.

Cohen, W. & Levinthal, D. (1990) “Absorptive Capacity: A New Perspective on Learning and Innovation.” *Administrative Science Quarterly,* 35(1): 128-152.

Cohen, W., Nelson, R., & Walsh, J. (2000) "Protecting Their Intellectual Assets: Appropriability Conditions and Why US Manufacturing Firms Patent (or Not)." Working paper no. w7552, National Bureau of Economic Research, Cambridge, MA.

Durlauf, S. (2001) "Manifesto for a Growth Econometrics." *Journal of Econometrics,* 10: 65-69.

Glasmeier, A., Markusen, A., & Hall, P. (1983) "Defining high Technology Industries," Working Paper No. 407, Institute of Urban and Regional Development, University of California, Berkeley.

Griliches, Z. (1992) "The Search for R&D Spillovers." *Scandanavian Journal of Economics,* 94 supplement: 29-47.

Howells, J. (2002) "Tacit Knowledge, Innovation, and Economic Geography." *Urban Studies,*39(5/6): 871-884.

Jaffe, A. (1989) "The Real Effects of Academic Research." *American Economic Review,* 79(5): 987-970.

Jaffe, A., Tratjenberg, M., & Henderson, R. (1993) "Geography, Location of Knowledge Spillovers as Evidence of Patent Citations." *Quarterly Journal of Economics,* 108: 483-499.

Keller, W. (2002) "Geographic Localization of International Technology Diffusion." *American Economic Review,* 92(1): 120-142.

Kirzner, I. (1979) *Perception, Opportunity and Profit: Studies in the Theory of Entrepreneurship*. Chicago: University of Chicago Press.

Kirzner, I. (1997) "Entrepreneurial Discovery and the Competitive Market Process: An Austrian Approach." *Journal of Economic Literature*, 35(1): 60-85.

Krugman, P. (1994) "Location and Competition: Notes on Economic Geography." In R. Rumelt, D. Schendel, & D. Teece, *Fundamental Issues in Strategy: A Research Agenda,* pp. 463-494. Boston: Harvard Business School Press.

Learner, E. & Storper, M. (2001) "The Economic Geography of the Internet Age." Working paper no. 8450. National Bureau of Economic Research, Cambridge, MA.

Mitchell, N. (2004) "Grad rates challenged." *Rocky Mountain News*, April 9

Nelson, R.R. (1992). "Schumpeter and Contemporary Research on the Economics of Innovation." In R.R. Nelson (ed) *The Sources of Economic Growth*, pp. 87-99. Cambridge: Harvard University Press.

Porter, M. E. (1991). “Towards a Dynamic Theory of Strategy.” *Strategic Management Journal*. 12: 95-117.

Ray, D. (1998) *Development Economics*. Princeton: Princeton University Press.

Romer, P. M. (1986) “Increasing Returns and Long-Run Growth.” *Journal of Political Economy,* 94(5): 1002-1037.

Romer, P. M. (1990) “Endogenous Technical Change.” *Journal of Political Economy*, 98(5): 71-102.

Solow, R. (1956) “A Contribution to Theory of Economic Growth.” *Quarterly Journal of Economics,* 70: 65-94.

Solow, R. (1957) “Technical Change and the Aggregate Production Function.” *Review of Economics and Statistics,* 39: 312-320.

Stinchcombe, A.L. (1965) "Social Structure and Organizations." In *Handbook of Organizations,* ed. J. G. March, 142-193. Chicago: Rand-McNally.

Varga, A. (1998) *University Research and Regional Innovation.* Boston: Kluwer.

Winter, S. (1984) “Schumpeterian Competition in Alternative Technological Regimes.” *Journal of Economic Behavior and Organization,* 5: 587-320.

Figure 1: LISA Cluster Map of Personal Income Growth in Colorado, 1990 to 2000
County growth rate in ( ), significance at 5% level

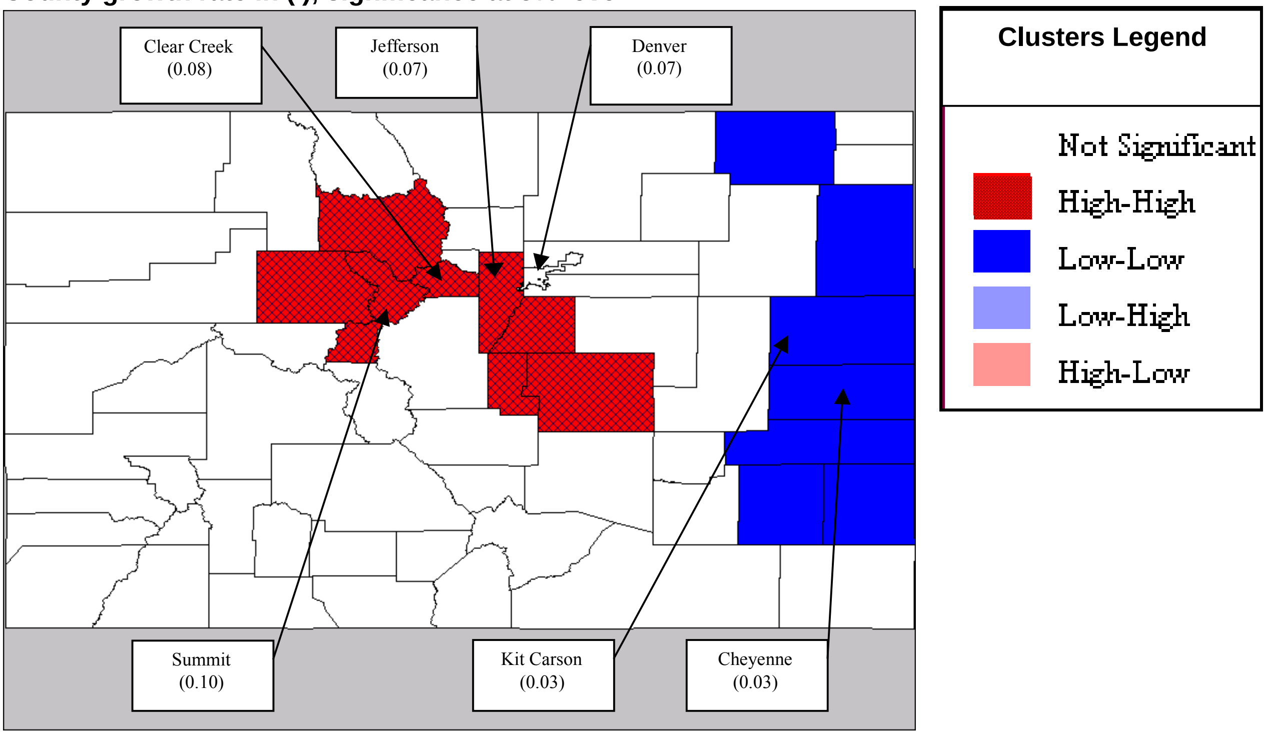

Table 1: Descriptive Statistics

Variable	Mean	STD	Min	Max
GROWTOT	0.07	0.03	-0.001	0.15
BOULDDUMM	0.02	0.13	0	1
DENDUMM	0.02	0.13	0	1
DENSITY	3.48	16.79	0.03	131.80
LOGINCTOT	12.49	1.75	9.31	16.52
KNOWLEDGE	0.004	0.01	0	0.03
RDDUMM	0.27	0.45	0	1
HTSBIRTHS	0.004	0.004	0	0.02
INCUMBENTS	0.01	0.01	0	0.08

Table 2: Correlations

Variable	1	2	3	4	5	6	7	8	9
1. GROWTOT	1.00								
2. BOULDDUMM	0.00	1.00							
3. DENDUMM	0.01	-0.02	1.00						
4. DENSITY	0.06	0.07	0.98	1.00					
5. LOGINCTOT	0.38	-0.11	0.27	0.29	1.00				
6. KNOWLEDGE	0.37	0.01	0.19	0.22	0.58	1.00			
7. RDDUMM	0.03	0.21	0.21	0.31	0.18	0.23	1.00		
8. HTSBIRTHS	0.21	-0.13	-0.02	-0.02	-0.18	0.17	-0.16	1.00	
9. INCUMBENTS	0.26	-0.07	0.13	0.12	0.45	0.32	0.03	0.16	1.00

Table 3: Spatial Regression Results for Colorado Personal Income Growth

1990 to 2000 (Average) **Colorado Counties (N = 63)**	**1**	**2**	**3**	**4**	**5**
KNOWLEDGE (K)	1.42 *	1.19 *	0.56	2.36 **	1.32
	(6.53)	(4.41)	(0.20)	(9.33)	(1.05)
RDDUMM	0.00	0.00	0.00	0.00	0.01
	(0.09)	(0.08)	(0.01)	(0.13)	(0.71)
HTSBIRTHS (λ)		0.77	0.44		0.09
		(1.09)	(0.20)		(0.01)
INCUMBENTS (θ)		0.25		0.32	0.19
		(0.78)		(1.42)	(0.41)
KNOWLEDGE * HTSBIRTHS			122.44		183.12
			(0.39)		(0.77)
KNOWLEDGE * INCUMBENTS				-0.01	-0.01 *
				(4.02)	(4.56)
Spatial Lag (ρ)	0.44 **	0.41 **	0.42 **	0.43 **	0.43 **
	(7.74)	(7.02)	(7.41)	(7.74)	(7.74)
Constant	0.03	0.03	0.03	0.03	0.03
R-Squared	0.25	0.29	0.28	0.31	0.33
Log-Lik	147.45	148.25	148.37	150.03	150.89
LM-Err	8.90 **	7.92 **	7.80 **	9.44 **	8.47 **
RLM-Err	0.00	0.00	0.16	0.07	0.24
LM-Lag	9.52 **	8.65 **	9.12 **	9.70 **	9.91 **
RLM-Lag	0.61	0.73	1.47	0.34	1.67
Jarque-Bera	0.26	0.21	0.07	0.76	0.37
Multicollinearity Condition Number	11.95	14.17	8.60	16.94	10.63
Breusch-Pagan	1.88	4.68	4.34	5.27	7.89
Koenker-Bassett	1.26	3.16	2.83	3.18	4.47

Significance: "*" at 5%, "**" at 1%, "***" at 0.1% level; Value of likelihood ratio in ( )

Table 4: Spatial Regression Results (with Controls) for Colorado Personal Income Growth

1990 to 2000 (Average) Colorado Counties (N = 63)	**6**	**7**	**8**	**9**	**10**
BOULDDUMM	-0.02	-0.01	-0.06	0.04	-0.03
	(0.50)	(0.28)	(3.30)	(1.48)	(0.35)
DENDUMM	0.11	0.17	0.19	-0.16	0.00
	(0.57)	(1.33)	(1.81)	(0.86)	(0.00)
DENSITY	0.00	0.00	0.00	0.00	0.00
	(0.74)	(1.69)	(2.27)	(0.99)	(0.00)
LOGINCTOT	0.01 *	0.01 **	0.01 **	0.01 *	0.01 ***
	(4.94)	(8.01)	(9.90)	(6.10)	(12.95)
KNOWLEDGE (K)	1.11	0.55	-1.92	2.35 **	-1.35
	(2.33)	(0.57)	(2.20)	(7.75)	(0.65)
RDDUMM	-0.01	-0.01	-0.01	-0.01	0.00
	(1.81)	(1.92)	(0.81)	(0.87)	(0.18)
HTSBIRTHS (λ)		1.65 *	-0.11		-0.24
		(4.80)	(0.01)		(0.05)
INCUMBENTS (θ)		0.02		0.12	-0.43
		(0.00)		(0.23)	(1.81)
KNOWLEDGE * HTSBIRTHS			522.31 *		609.23 *
			(5.13)		(4.56)
KNOWLEDGE * INCUMBENTS				-0.02 **	-0.02 *
				(7.57)	(4.11)
Spatial Lag (ρ)	0.41 **	0.40 **	0.36 *	0.39 **	0.36 *
	(7.20)	(6.95)	(5.81)	(6.94)	(6.29)
Constant	-0.04	-0.08	-0.07	-0.05	-0.09
R-Squared	0.40	0.44	0.48	0.47	0.52
Log-Likelihood	150.78	153.37	155.93	154.76	159.31
LM-Err	8.46 **	6.84 **	5.71 *	8.64 **	6.23 *
RLM-Err	0.26	0.00	0.00	0.32	0.02
LM-Lag	8.54 **	8.28 **	7.17 **	8.69 **	8.17 **
RLM-Lag	0.34	1.43	1.46	0.37	1.96
Jarque-Bera	2.61	1.98	1.78	3.18	2.23
Multicollinearity Condition Number	19.81	22.98	23.06	26.54	32.07
Breusch-Pagan	6.23	5.28	8.16	9.78	13.58
Koenker-Bassett	5.22	4.34	5.74	6.24	7.53

Significance: "*" at 5%, "**" at 1%, "***" at 0.1% level; Value of likelihood ratio in ( )

Appendix: High Technology Industries according to R&D, employment, and innovation criteria (Source: Varga, 1998)

Industry (SIC classification)	SIC	NAICS Codes
Crude petroleum and natural gas	131	21111
Industrial inorganic chemicals	281	21111, 32512, 32513, 32518, 32599, 33131
Plastic materials and synthetics	282	32521, 32522
Medicinals and botanicals	283	32541
Soap	284	32561, 32562
Paints	285	32551
Industrial organic chemicals	286	32511, 32513, 32519
Agricultural chemicals	287	32531, 32532
Miscellaneous chemical products	289	31194, 32518, 32519, 32551, 32552, 32591, 32592, 32599
Petroleum refining	291	32411
Reclaimed rubber	303	
Ordnance and accessories not elsewhere classified	348	33299
Engines and turbines	351	33361, 33639
Construction and related machinery	353	33243, 33299, 33312, 33313, 33392, 33651
Metal working machinery	354	33221, 33299, 33351, 33399, 33531
General industrial machinery	356	31499, 33299, 33341, 33361, 33391, 33399
Computer and office equipment	357	33331, 33411, 33441, 33451, 33461, 33994
Electronic distribution equipment	361	33531
Electrical industrial apparatus	362	33531, 33599
Household appliances	363	33329, 33341, 33521, 33522, 33999
Electric lighting and wiring	364	33221, 33511, 33512, 33593, 33632
Audio and video equipment	365	33431, 33461, 51222
Communications equipment	366	33421, 33422, 33429, 33441
Electronic components and accessories	367	33422, 33431, 33441
Miscellaneous electrical equipment and supplies	369	33319, 33361, 33399, 33461, 33512, 33591, 33599, 33632
Aircraft and parts	372	33641, 54171
Railroads	374	33391, 33651
Guided missiles and space	376	33641, 54171
Search and navigation equipment	381	33451, 33911
Measuring and controlling devices	382	33331, 33451, 33911
Optical instruments and lenses	383	
Medical instruments and supplies	384	32229, 33299, 33451, 33911
Ophthalmic goods	385	33911
Photographic equipment and supplies	386	32599, 33331
Communication services not elsewhere classified	489	48531, 51332, 51334, 51339
Computer and data processing services	737	33461, 44312, 51121, 51419, 51421, 51811, 51821, 53242, 54151, 81121
Research and development and testing services	873	54138, 54171, 54172, 54191, 54194