On the Company We Keep: Combined Scale-and-Scope Externalities in the Growth of IT Industry Co-Agglomerations

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Abstract. Most information technology (IT) industry clusters exhibit the *co-agglomeration* of several industries. We propose that the synergies between industries do not only consist of separate *scale effects* and *scope effects*. They also exhibit *combined scale-and-scope effects* or externalities, so the scale of one industry affects others' growth. Our study analyzes the co-agglomeration of four IT industries in 3,142 counties in the United States. Using econometric methods, we find that the co-agglomerated computer manufacturing industry benefits the growth of the semiconductors manufacturing industry. Similarly, collocated firms in the semiconductors manufacturing and computer systems design industries appear to benefit each other. We find little evidence like this for the software publishing industry though. Our study offers policy implications for industrial development planners in the global economy.

Keywords and phrases: Agglomeration, co-agglomeration, combined scale-and-scope effects, empirical analysis, externalities, growth, innovation, IT industries, scale, scope.

1. INTRODUCTION

Growth patterns of IT industries are of strategic importance to the economic growth of a country. Iammarino and McCann [42, p. 1019] assert: "The contemporary geography of innovation is essentially a geography of the currently more innovative sectors of economy." DeVol [21] posits that in similar metropolitan areas in the U.S., growth in the high-tech explains nearly 70% of the variation in relative economic growth. Hanna [34] argues that IT is a strategic sector which can transform developing countries into modern global economy.

Recognizing the importance of IT industries to the economic development, countries all over the world are setting up "IT parks," "technology parks," or similar infrastructure facilities. Examples include the Hsinchu Science-based Industrial Park in Taiwan [41], Mjärdevi Science Park in Sweden [40], and Kista Park in Finland [60]. The IT park model appears to help growth of IT industries, but a clear understanding of the benefits which accrue is not well understood. The objective of this article is to study the nature of externalities that exist between co-agglomerated IT industries and why they can explain growth. *Agglomeration*—the phenomenon of economic activity congregating in or close to a single location, rather than being spread out uniformly over space—results in increasing returns to scale and increasing productivity. By *co-agglomeration*, we refer to the collocation of two or more different economic activities.

We study the growth of four different IT industries: computer and peripheral equipment manufacturing (abbreviated as computer manufacturing), semiconductor and other electronic components manufacturing (semiconductors manufacturing), software publishing (software), and computer systems design and related services (computer systems design). We address the following research questions for the selected IT industries. (1) Does co-agglomeration of different IT industries influence innovation and growth in them? (2) What theoretical perspective can explain the existence of the combined scale-and-scope effects between different IT industries? If so, what roles do scale and scope externalities play? (3) Is there evidence to suggest a combined scale-and-scope effect on the growth of IT industries?

§2 provides an overview of our theoretical perspective and research review to guide development of our hypotheses. §3 explains the research model, methods and data. §4 presents our empirical analysis and econometric results to test for combined scale-and-scope externality effects. §5 offers several different interpretations of the results. §6 concludes with contributions and limitations.

2. THEORETICAL PERSPECTIVES

2.1. MAR and Jacobs Externalities

Agglomeration occurs as positive *externalities* develop amongst collocated economic entities. Previous agglomeration literature recognizes that externalities occur among firms that are located in close proximity to one another [38,39]. *Positive externalities* develop within the same industry or across different industries, leading to *endogenous growth* [2]. Economists Marshall [51], Arrow [4] and Romer [61] have separately posited that externalities occur within individual industries: *MAR externalities*. Jacobs [43] has argued that externalities also occur between different industries: *Jacob externalities* [30]. MAR externalities represent *economies of scale*: thus, it is advantageous for an industry to specialize in one particular activity yielding what are called *scale externalities*. Jacobs externalities come from *economies of scope*: it pays to combine a set of heterogeneous but complementary activities in a region, and so there is the possibility of *scope externalities* across industries. The Jacobs externalities (scope) effect has been studied in prior literature primarily to capture the influence from variety of agglomerated industries.

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Scope externalities have been examined in the context of overall diversity. Glaeser et al. [30] estimated scope externalities in terms of variety of industries in the city outside the industry in question. Moreno et al. [54] proposed a measure of overall diversity to assess Jacob externalities. The *influence of one industry on another collocated industry* has become a focus of attention in more recent works, such as Ellison et al. [24]. It is this complementary effect that we try to examine in the context of co-agglomerated IT industries.

2.2. The Heterogeneous Nature of IT Agglomerations

The concentration of IT industries is striking. Not only do certain pockets have high concentrations of IT industries, these concentrations have a heterogeneous mix of IT industries. For example, Santa Clara County in California occupies less than 1% of the area of the state, and has less than 5% of its population, yet it has nearly 45% of the state's computer manufacturing industry, around 23% of the state's semiconductors manufacturing industry and nearly 32% of the state's software industry. The heterogeneous nature of IT industrial agglomerations is not unique to the U.S. but is seen the world over. For example, the high-tech region of Cambridge in the United Kingdom has a heterogeneous mix of several IT industries [32]. Nokia in Kista Park, Finland and Ericsson in Stockholm, Sweden have large IT industries that are not directly tied to wireless industries [60]. The IT agglomerations in the Indian cities of Mumbai, Bangalore and Hyderabad also have heterogeneous mixes [44].

2.3. IT Industry Co-Agglomeration Hypotheses

Studies and real-world observations suggest the presence of scale externalities in IT industries. The dominant players within each industry are indicative of scale-size effects: Intel, AMD and Motorola within semiconductors; Compaq, Dell and IBM in computer manufacturing; and Microsoft and Apple in operating systems. These companies have achieved scale economies in each location of operation, even as they have expanded to different locations. For example, Microsoft signed a development agreement with the City of Redmond in January 2005 to add two million square feet on and around its Redmond campus over the next 10 to 20 years. As Brad Smith, SVP, Microsoft [52] has stated: "[This] allows us to maintain close proximity among our core product development teams, as well as maximize efficiencies of existing campus and related infrastructure." This is clear evidence of a company leveraging on scale externalities.

Similar findings are reported by Weterings and Koster [72]. They studied growth and survival of software firms and found that founders who set up these firms near previous work places benefited also. Rosenkopf and Almeida [62] demonstrated the localization of knowledge in semiconductors. Arthur [5] also found evidence for agglomeration effects in the computer chip industry. Beardsell and Henderson [9] reported evidence of significant *own-industry externalities* for single-plant firms but also found that corporate plants for computers are more self-reliant and less influenced by externalities. Silvente and Gimènez [66] also found evidence of scale externalities for export-oriented businesses in Spain.

Scope externalities due to overall diversity of collocated industries have been reported to influence industrial growth. Since urban areas represent diverse economic activity, urbanization is associated with existence of scope externalities. Bettencourt et al. [12] found increasing returns to inventive activity for larger urban areas. Garcia-Vega [28] found that both R&D intensity and patents increase with the degree of technological diversification of firms in Europe. Glaeser et al. [30] compared six two-digit industries in the U.S. and reported that diversity helps growth. Chen [18], who studied city-industry externalities in Taiwan, reported similar results. Van Oort and Atzema [71] looked at factors that determined IT firm formation in Holland and found heterogeneity for localized firm formation.

Other studies have found evidence for both types of externalities. Fu [27] argued that individual workers learn due to both these externalities. Moreno et al. [54] tested for existence of both scale and scope externalities in agglomerations across Europe and found evidence of both. Girma and Wakelin [29] also found evidence of intra-industry and inter-industry spillovers between domestic plant's productivity and foreign direct investment in the electronics sector in the U.K.

Thus, MAR (scale) and Jacobs (scope) externalities should exist among collocated IT industries and these externalities may vary across industries. We propose:

- **Hypothesis 1a (Existence of Scale (Scope) Externalities in Agglomerated IT Industries).** *Agglomerated IT industries experience scale (scope) externalities which facilitate their growth.*
- **Hypothesis 1b (Degree of Externalities for Different IT Industries).** *The effects of scale (scope) externalities for different IT industries are different.*

Competition. Porter [57] argued that the scale externalities are facilitated by local competition, rather than by monopolies. Tang [69] asserted that firms' perceptions about their competitive environment are important determinants of innovation. Autant-Bernard [8] on the contrary found that a low level of competition in the target region increases the probability of a firm setting up its R&D facilities in a region. Having noted the mixed findings here, we test the following hypotheses:

- **Hypothesis 2 (Competition among Agglomerated IT Industry Firms).** *Competition among collocated firms in an IT industry facilitates industry growth.*

2.4. Combined Scale-and-Scope Effects

We next explore the co-agglomeration externalities between co-agglomerated IT industries. To recognize the co-agglomeration externalities between different IT industries, it is relevant to review the historical evolution of the industries. The computer manufacturing industry has undergone a change from the *vertical industry structure* of the 1970s and 1980s to a *horizontal industry structure* in the 1990s. The vertical structure era had players such as IBM and Digital Equipment Corporation dominating the international market. As the number of applications for computers or semiconductors or software increased, it resulted in vertical disintegration of the vertically-integrated computer manufacturing industry into several industries: computer manufacturing, semiconductors manufacturing, and software and computer services [14].

Even though the IT industries are now specialized, they continue to have linkages. The semiconductor industry continues to have *backward linkages* and *forward linkages* with computer manufacturing and software. Innovation in the semiconductor industry led to exponential growth in the memory capacities of chips. This had a direct impact on the number of lines of code which chips could contain. With increased semiconductor capacity, software complexity and performance abilities increased [64]. Innovation in semiconductors also made computers more powerful, with ability to process more information faster. These linkages gave rise to indirect network effects between different IT industries which cause IT agglomerations.

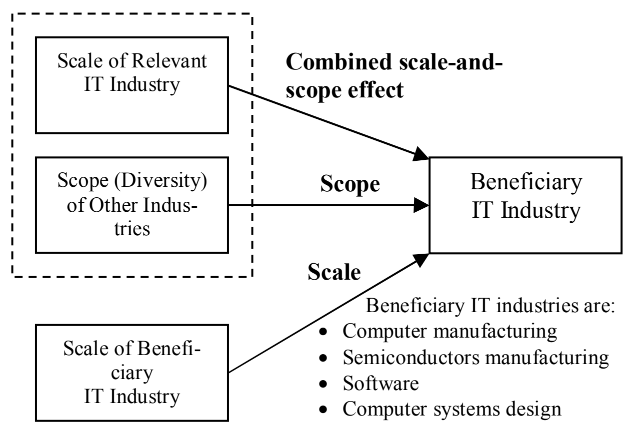
Knowledge spillovers take place through trade [7, 25] and since semiconductors and other electronic components are inputs to computer manufacturing, the trade between semiconductors and other electronic components manufacturers and computer manufacturers provides opportunities for knowledge spillovers. Spillovers also take place through the movement of employees, especially engineers and scientists [3, 7]. Engineers and scientists are among the most mobile segments of the workforce. Mobility of engineers and scientists between these industries is a related source of externality through labor pooling and knowledge spillovers.

There is yet another linkage between the semiconductor manufacturing and software industries. Chip design has become increasingly similar to software design [19]. Hardware circuits are described using modeling or programming languages, and they are validated and implemented by executing software programs, which are conceived in support of specific circuit designs. Designing semiconductors requires designers to be knowledgeable in both the hardware and software domains to make good design tradeoffs.

Guiso and Shivardi [33] argued that information spillovers occur through social interactions between collocated and similar firms with common problems. With linkages between the IT industries, information spillovers may also exist between closely related industries when they are co-agglomerated. The underlying rationale for combined scale-and-scope effects from one IT industry to another is that these industries have synergies. This influence is heightened when the assets are collocated. A microeconomics-based search-theoretic framework for synergy between different IT industries has been proposed by Berliant et al. [11]. They noted that agents with differentiated types of knowledge search for partners and exchange ideas that improve production efficiency. This leads to synergies between some industries. So other than own-industry scale (MAR) externalities, and other-industry Jacobs (scope) externalities, some IT industries may be influenced by scale effects in another IT industry. We call this *combined scale-and-scope effects.* (See Fig. 1.) Thus, we propose:

- **Hypothesis 3 (Combined Scale-and-Scope Effects Hypothesis).** *Combined scale-and-scope effects exist due to economies of scale in other co-agglomerated IT industries.*

Fig. 1. Externality Effects of IT Co-Agglomeration



3. MODEL, DATA AND METHODS

3.1. Estimation Model and Key Variables

Model. A Hick's neutral production function for an establishment can be written as $g(A)f(L)$, where L represents labor inputs and $g(A)$ depends on the technology of production. A represents the effect of agglomeration on the technology of production. If agglomeration externalities exist, and lead to innovation and growth, the corresponding representation of $g(A)$ should be significant. Since each firm maximizes profit, the wage rate of labor at time t will be equal to the marginal product of labor at time t, or $g(A_t) \cdot f'(L_t) = w_t$, where w_t represents the wage rate at time t. Assuming a Cobb-Douglas functional form for the firm's production function, $f(L) = L^{1-\alpha}$ with $0 < \alpha < 1$. In terms of growth rates, we obtain: [1]

[1] This is a well-accepted way to model the input-output growth relationship. It permits us to incorporate agglomeration and co-agglomeration variables as inputs in the production process, as

$$\alpha \log\left(\frac{L_{t+1}}{L_t}\right) = -\log\left(\frac{w_{t+1}}{w_t}\right) + \log\left(\frac{g(A_{t+1})}{g(A_t)}\right) + \varepsilon_{t+1} \quad (1)$$

Assume further that agglomeration externalities grow at a rate exogenous to the firm. Representing the term $\log\left(\frac{g(A_{t+1})}{g(A_t)}\right)$ as the *externalities function $F_i(\bullet)$ for an industry i,* we conceptualize $F_i(\bullet)$ as explained by: (1) the level of *labor specialization* in industry *i* ($SPCLN_i$) representing scale (MAR) externalities; (2) the degree of *competition among firms* in industry *i* ($COMPTN_i$); (3) scope (Jacobs) externalities represented by the overall diversity of all industries (*DIVERSITY*) and (4) the combined scale-and-scope externality effects from other IT industries in the agglomeration ($j \neq i$) $SPCLN_j$ and their interactions, Π_j *SPCLN*. Thus $F(\bullet) = F(SPCLN_i, COMPTN_i, DIVERSITY, \Pi_j SPCLN_j)$.

The constructs *SPCLN, COMPTN* and *DIVERSITY* are defined as in Glaeser et al. [30]:

$$SPCLN_i = \frac{\text{Employment in industry } i \text{ in aggl/Total employment in aggl}}{\text{Employment in industry } i \text{ in US/Total employment in US}}$$

$$COMPTN_i = \frac{\text{Firms in industry } i \text{ in agglo/employment in industry } i \text{ in aggl}}{\text{Firms in industry } i \text{ in US/employment in industry } i \text{ in US}}$$

$$DIVERSITY = \frac{\text{Std. dev. of average emp in different 2 digit level industries in aggl}}{\text{Average emp in different 2 digit level industries in aggl}}$$

Control Variables. Blume [13] found that local economic policies explain some of the variation in the local business climate and growth of industries. Policies may be *fiscal* (financial) or *non-fiscal*. We use unemployment rate (*UNEMP*) to proxy for local labor market efficiency [56]. We use the local sales tax rate (*TAX*) as a proxy for local fiscal policy for the industry [23]. Another important determinant of the location of firms is the local market-size [8]. We use the local population (*POP*) [15] and rural/urban county (*URBAN*) to proxy for that [10].

3.2. Estimation Issues

One difficulty in estimations for externalities as a determinant of agglomerations is the likelihood of *endogeneity*. This leads to inconsistent estimation results. One reason is that some contemporaneous shocks to an agglomeration affect focal industry and other industries' growth in the agglomeration. This could introduce bias in the results [59]. The likelihood of such shocks, however, will diminish if the unit of analysis is smaller. By using *county* as the analysis unit, the likelihood of such contemporaneous shocks is reduced [36]. Endogeneity may also occur if there is *reverse causality*. One may argue that more productive and growth-oriented firms seek highly productive regions. It is difficult to find good instrumental variables though: it always can be argued that most instrumental variables may be correlated with the error term also [63].[2]

Though it is difficult to totally rule out endogeneity, our effort in this estimation is to control for its possible negative impacts as much as possible. We adopt a small unit of analysis which reduces likelihood of endogeneity due to contemporaneous shocks. We use state-level fixed effects to control for unobserved state-level factors which may cause firms to locate in specified states. We also use several data sets. One relates to counties with all four IT industries co-agglomerated. The others relate to counties with at least two focal IT industries which are co-agglomerated. We also study co-agglomeration-driven growth across different time periods of IT growth, ranging from three to six years. The main results for these estimations are broadly consistent in that they typically have similar fits, significant variables and parameter valences. Also, since we use a system of equations, the error term of one equation is not required to be uncorrelated with the error terms of other equations. It suffices if it is uncorrelated with the change in the regressor function. This is not a very strict requirement. Selecting only those areas which are highly agglomerated IT centers would introduce a selection bias, so we considered all counties in the United States.

Industry Choices, Unit of Analysis. Based on the well-accepted NAICS classification, we selected several IT industries:[3] computer and peripheral equipment manufacturing (NAICS 33411), semiconductor and other electronic components manufacturing (NAICS 33441), software publishing (NAICS 51121), and computer systems design and related services (NAICS 54151). Thus we have two manufacturing industries and two service industries. Our unit of analysis is the industry, by county, for different periods of time.[4]

Data Sources. We use the County Business Pattern data of the U.S. Census Bureau for employment levels in

in past studies. Other complex production forms like the *constant elasticity of substitution* (CES), *translog*, or *translog-CES* production forms would b relevant if we were interested in production and inputs, such as labor and capital.

[2] Henderson [39] used local environment measures like *market potential* and *air quality*, Ades and Glaeser [1] used *political stability* and *political rights*, Carlton [16, 17] used *public policy*, and Audretsch and Feldman [6] used *natural resources* and *transportation costs* as instruments. These studies recognized that it is difficult to find good instrumental variables for the study of industry agglomeration.

[3] The NAICS classification replaced Standard Industry Codes (SICs) in the recent past, and is frequently used in current studies that involve the analysis of production, profitability and technological change in U.S. industries.

[4] The NAICS classification also supports effective empirical analysis because the U.S. government collects data for each industry for different geographical units: the county, state and country levels. The U.S. Census Bureau provides the most extensive source of data that is available at the county level, and is currently unmatched by any other source.

identified industries and total employment in each county. The annual population estimates for each county were collected from the Regional Economic Information System of the Bureau of Economic Analysis. The annual sales tax rates for each state were collected from the Tax Foundation, Washington, DC (www.taxfoundation.org). Unemployment rates were obtained from the Local Area Unemployment Statistics of the Bureau of Labor Statistics. Urban counties were identified based on the definition of MSAs issued on June 30, 1999.

Summary Statistics. The summary statistics of the counties with specified IT industries are in Table 1.

Table 1. County Summary Statistics, IT Industries

YEAR	NUMBER OF COUNTIES	EMPLOYMENT			
		Mean	*Std. Dev.*	*Min.*	*Max*
Computer and Peripheral Equipment Manufacturing					
1998	449	577.78	2,316.6	1	36,666
2004	396	336.31	1,043.4	7	8,730
Semiconductor and Other Electronic Components Mfg.					
1998	893	674.63	2,886.2	10	62,701
2004	826	469.63	1,738.6	10	26,805
Software Publishing					
1998	913	313.83	1,421.6	2	25,682
2004	788	425.87	2,021.9	7	36,052
Computer Systems Design and Related Services					
1998	1921	460.14	2,107.6	1	43,509
2004	2066	534.62	2,520.0	1	61,095

Notes. The data relate to 50 states (including Hawaii and Alaska) and Washington, DC. It does not include Puerto Rico. The total number of counties is 3,142. The *mean employment* is calculated for counties in which the industry exists. The counties in which the industry does not exist have been excluded from the mean employment calculation. The source of the data is County Business Patterns, U.S. Census Bureau.

The two IT manufacturing industries, computers and semiconductors manufacturing, show declining trends in terms of the number of counties and the average number of employees in the counties in which these industries exist. However, the IT service, software, and computer systems design industries show a corresponding increase in average employment in the counties in which they exist. The software industry shows a decline in the number of counties in which it exists, but the computer systems design industry has expanded. The statistics show that most counties which have computer manufacturing industry also have the other three IT industries studied. For example, in 1998, 316 out of 447 counties (around 70%) had all four IT industries. In 2004, the corresponding number was 275 out of 396 (around 69.5%). Thus, the IT agglomerations seem to co-agglomerate.

4. ESTIMATION RESULTS

4.1. Model Specification

See Table 2 for the modeling notation. The main consideration for finalizing the model was to have explanatory power while observing parsimony.

Table 2. Modeling Notation

VARIABLE	DESCRIPTION
$Empl_{1,\,t1}$	Employment in computer manufacturing industry at time t_1
SPCLN	Specialization
DIVERSITY	Diversity
COMPTN	Competition
WAGES; POP	Wages; population
TAX; UNEMP	Sales tax rate; unemployment rate
$\alpha, \beta, \gamma, \delta; \varepsilon$	Parameter estimates; error term

The final estimation model specification includes all four IT industries. [5] Subscripts are: 1 = computer manufacturing, 2 = semiconductors manufacturing, 3 = software and 4 = computer systems design, as shown below:

- **Model for computer manufacturing industry (1)**

$$\ln(Empl_{1,t1}/Empl_{1,t0}) = \alpha_0 + \alpha_1 \cdot SPCLN_1 + \alpha_2 \cdot DIVERSITY + \alpha_3 \cdot COMPTN_1 + \alpha_4 \cdot WAGES_1 + \alpha_5 \cdot SPCLN_2 + \alpha_6 \cdot SPCLN_3 + \alpha_7 \cdot SPCLN_4 + \alpha_8 \cdot POP + \alpha_9 \cdot TAX + \alpha_{10} \cdot UNEMP + \alpha_{11} \cdot URBAN + \varepsilon_1$$

- **Model for semiconductor mfg. industry (2)**

$$\ln(Empl_{2,t1}/Empl_{2,t0}) = \beta_0 + \beta_1 \cdot SPCLN_2 + \beta_2 \cdot DIVERSITY + \beta_3 \cdot COMPTN_2 + \beta_4 \cdot WAGES_2 + \beta_5 \cdot SPCLN_1 + \beta_6 \cdot SPCLN_3 + \beta_7 \cdot SPCLN_4 + \beta_8 \cdot SPCLN_1 \cdot SPCLN_4 + \beta_9 \cdot SPCLN_1 \cdot SPCLN_2 + \beta_{10} \cdot SPCLN_1 \cdot SPCLN_3 + \beta_{11} \cdot SPCLN_2 \cdot SPCLN_4 + \beta_{12} \cdot SPCLN_2 \cdot SPCLN_3 + \beta_{13} \cdot SPCLN_3 \cdot SPCLN_4 + \beta_{14} \cdot POP + \beta_{15} \cdot TAX + \beta_{16} \cdot UNEMP + \beta_{17} \cdot URBAN + \varepsilon_2$$

- **Model for software industry (3)**

$$\ln(Empl_{3,t1}/Empl_{3,t0}) = \gamma_0 + \gamma_1 \cdot SPCLN_3 + \gamma_2 \cdot DIVERSITY + \gamma_3 \cdot COMPTN_3 + \gamma_4 \cdot WAGES_3 + \gamma_5 \cdot SPCLN_1 + \gamma_6 \cdot SPCLN_2 + \gamma_7 \cdot SPCLN_4 + \gamma_8 \cdot SPCLN_1 \cdot SPCLN_1 + \gamma_9 \cdot SPCLN_2 \cdot SPCLN_2 + \gamma_{10} \cdot SPCLN_3 \cdot SPCLN_3 + \gamma_{11} \cdot SPCLN_4 \cdot SPCLN_4 + \gamma_{12} \cdot POP + \gamma_{13} \cdot TAX + \gamma_{14} \cdot UNEMP + \gamma_{15} \cdot URBAN + \varepsilon_3$$

- **Model for computer systems design industry (4)**

$$\ln(Empl_{4,t1}/Empl_{4,t0}) = \delta_0 + \delta_1 \cdot SPCLN_4 + \delta_2 \cdot DIVERSITY + \delta_3 \cdot COMPTN_4 + \delta_4 \cdot WAGES_4 + \delta_5 \cdot SPCLN_1 + \delta_6 \cdot SPCLN_2 + \delta_7 \cdot SPCLN_3 + \delta_8 \cdot SPCLN_1 \cdot SPCLN_2 + \delta_9 \cdot SPCLN_1 \cdot SPCLN_3 + \delta_{10} \cdot SPCLN_1 \cdot SPCLN_4 + \delta_{11} \cdot SPCLN_2 \cdot SPCLN_3 + \delta_{12} \cdot SPCLN_2 \cdot SPCLN_4 + \delta_{13} \cdot SPCLN_3 \cdot SPCLN_4 + \delta_{14} \cdot SPCLN_1 \cdot SPCLN_1 + \delta_{15} \cdot SPCLN_2 \cdot SPCLN_2 + \delta_{16} \cdot SPCLN_3 \cdot SPCLN_3 + \delta_{17} \cdot SPCLN_4 \cdot SPCLN_4 + \delta_{18} \cdot POP + \delta_{19} \cdot TAX + \delta_{20} \cdot UNEMP + \delta_{21} \cdot URBAN + \varepsilon_4$$

We tested for multicollinearity of the independent variables in the selected models using the variance inflation factor (VIF). The VIF estimates above 10 are a matter of

[5] We carried out the Ramsey regression equation specification error test [58] for omitted variables. It shows if interaction and higher-order terms of variables would improve the specification. This led to specification of our final model with no omission. The Akaike information criterion (AIC) and the Schwarz Bayesian information criterion Values (SBIC) also indicated parsimony and appropriateness of the selected models.

concern. The selected models have mean VIF which range from 1.40 to 4.42. This removes any serious multicollinearity concerns. A key issue is the information structure of the setting [49]. To this end, we tested for heteroskedasticty, normality and autocorrelation in the error structure. We used the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity. The results show that the error structure for all industries except computer systems design industry is heteroskedastic. This is not surprising considering that there is huge variation in the distribution of these three industries. We accordingly use feasible generalized least squares for robust estimations of these industries. The distribution of variables for all the four IT industries is found to be non-normal. Therefore, we rely on asymptotic assumptions for consistent estimates. We calculated IT industry growth levels for the following three-year time intervals: 1998-2001, 1999-2002, 2000-2003 and 2001-2004. [6]

4.2. Model Estimation

We employed several different econometric testing methods. Chief among them was *seemingly unrelated regression* (SUR). With two or more different equations, one for each industry in a county, and each equation related to others via the error term of unaccounted influences, SUR provides more efficient estimation. We also employed *feasible generalized least squares* (FGLS), which estimates a covariance matrix and does not assume one. It is possible that there are state-specific effects, since different states create separate economic environments that are subject to different corporate tax and wage tax laws. Thus, we also estimated panel data with state-specific fixed effects. This shows if there are state-specific or group-wise heteroskedastic effects [26].

Our results show the existence of scale (MAR) and scope (Jacobs) externalities in selected IT industries. The effects we observe appear to be different for different IT industries. We also find evidence for combined scale-and-scope effects. We tested the externality effects for three, four, five, and six-year time intervals. The results for the three, four and six-year estimation of FGLS and SUR estimations are shown in Table 3 (included at the end).[7] All the models were significant across different estimation methods with reasonably high R^2 values between 10% and 60%. For estimations involving macroeconomic phenomena these values indicate very good fit.

[6] The periods included overlapping years, so we tested for first-order serial autocorrelation using the Durbin-Watson (DW) test. A DW statistic less than 2 indicates positive autocorrelation. The DWs for the IT industries range from 1.14 to 1.42. Since autocorrelation between successive periods may occur, we do not pool observations, and instead use non-overlapping periods of 1998-2001 and 2001-2004 in our estimations.

[7] Other results are not shown for lack of space, but are generally consistent with what we presented here.

The fit also seems to improve for SUR regressions, indicating that the error structure for the four IT industries is correlated and supports the SUR model.

The results of our regression equations support the argument that agglomeration externalities, as represented by our dependent variables, help explain the growth of collocated IT industries. The externalities also appear to be different for different IT industries, based on the significance of the estimated coefficients. Thus, the Existence of Externalities for Collocated IT Industries Hypothesis (H1a) and the Degree of Externalities for Different IT Industries Hypothesis (H1b) both are supported.

We also find competition to be significant in all our estimations. However, the effect of competition is negative, for most part, suggesting agglomerations with low competition witness higher growth in specified IT industries. Thus the evidence, while pointing to the significance of competition, does not support the Competition among IT Industry Firms Hypothesis (H2). Our results here match Autant-Bernard [8], who posited that firms tend to concentrate R&D activities in regions with low competition. The results also suggest increased concentration in the industrial organization of these industries. This is in accordance with what we see in real life—the growth of large companies in each IT industry, for example, Microsoft, Oracle, Intel, AMD, Motorola, Dell, IBM, Accenture, Wipro, and so on.

The results also point to significant combined scale-and-scope effects. Semiconductors manufacturing seems to benefit from the co-agglomerated computer manufacturing industry for all estimations and across different time intervals. Further, semiconductors manufacturing and computer systems design benefit from each other's presence. (See Table 3.) We also find that the effect of some industries is negative on the growth of others. Though we did not specifically hypothesize about possible negative effects, the result in this regard is not particularly surprising. When certain industries become too agglomerated, this may lead to congestion externalities [46], which may further set up the basis for diminishing agglomeration. For IT industries, congestion may arise in terms of shortage of skilled manpower or excess supply shocks as witnessed during the pre-2001 dotcom boom. The consequent bust affected IT industries all around. The IT industries also witnessed large-scale outsourcing during the period of study and a decline in employment might be attributed to this [22]. In the context of these reverses, positive growth is of greater significance. Overall, this supports our Combined Scale-and-Scope Effects Hypothesis (H3).

4.3. Sensitivity Analysis

To verify the robustness of our results, we carried out several alternative analyses. We test for externality effects on an expanded dataset to include counties where at least two of the focal IT industries are co-agglomerated.

We study the relationships between (1) computer manufacturing and semiconductors manufacturing and (2) semiconductors manufacturing and computer systems design industries. (See Table 4.)

Table 4. Externalities for More Counties

EXTERNALITY TYPES	STRONGLY-RELATED INDUSTRIES	
***Computer Mfg.* (1) *and Semiconductor Mfg.* (2)**		
Collocation	**(1)**	**(2)**
CSS		*$SPCLN_2$* (+) *
*R*2	28.8%	27.7%
P > F	0.019	0.001
***Semiconductor Mfg.* (2) *and Computer Sys. Design* (4)**		
Collocation	**(2)**	**(4)**
Scale	*$COMPTN_2$* (-)** *$SPCLN_2$* (-)*	*$COMPTN_4$* (-)***
Scope		*DIVERSITY* (-)**
CSS		*$SPCLN_2$* (-) *** *$SPCLN_2$* (+)* *$SPCLN_4$* (+)*
R^2	10.6%	20.4%
P > F	0.029	0.001

Notes. CSS: Combined scale- and-scope. SUR estimation only. Only significant coefficients are presented. Control variables have been omitted for brevity. Signif: * $p < .10$, ** $p < .05$, *** $p < .01$.

The results are consistent with our previous results. A presence of computer manufacturing seems to facilitate growth of the semiconductors manufacturing industry. This validates our combined scale-and-scope effect between the semiconductors manufacturing and the computer manufacturing industries. Similarly, the presence of the semiconductors manufacturing industry seems to facilitate the growth of computer systems design industry. Overall, the empirical analysis suggests that there are combined scale-and-scope externalities between IT industries, and so our third hypothesis is supported.

5. INTERPRETATION AND DISCUSSION

The hypotheses and findings are in Table 5.

Table 5. Hypotheses and Findings

HYPOTHESES	RESULTS
Hypothesis 1a (Existence of Scale (Scope) Externalities in Agglomerated IT Industries). *Agglomerated IT industries experience scale (scope) externalities which facilitate their growth.*	Supported
Hypothesis 1b (Degree of Externalities for Different IT Industries). *The effects of scale (scope) externalities for different IT industries are different.*	Supported
Hypothesis 2 (Competition among Agglomerated IT Industry Firms). *Competition among collocated firms in an IT industry facilitates industry growth.*	Not supported
Hypothesis 3 (Combined Scale-and-Scope Effects Hypothesis). *Combined scale-and-scope effects exist due to the economies of scale of other co-agglomerated IT industries.*	Supported

The growth of IT industries is key to economic and social development in developing countries. We provide evidence in support of agglomeration for the growth of IT industries. Agglomeration of IT industries is important, but co-agglomeration which provides externalities, over and above agglomeration externalities, further promotes the growth of some IT industries. Agglomeration is viewed as important because the interactions between collocated industries form an important part of the innovation process [70]. The results reflect that even though communication costs have gone down and IT permits remote collaboration, face-to-face interactions remain an important element in innovation and growth in IT industries [48, 55].

This is possibly due to ambiguity and uncertainty related to creation of new knowledge and is the reason for the continued existence of agglomerations of IT industries [41]. Hansen [35] stressed that while weak ties are adequate for transfer of knowledge when it is not complex, they are not enough when the knowledge to be transferred is complex. Developing this theme further, Sorenson et al. [67] posited that industries which rely on complex knowledge are likely to agglomerate as ties are likely to be stronger when the firms are collocated. Though several scholars have suggested the role of scale (scope) in growth of these industries, this study suggests that combined scale-and-scope effects between co-agglomerated IT industries are also important for growth of IT industries. It also provides a methodology to measure the size of the combined scale-and-scope effects between co-agglomerated industries.

The conceptual basis for combined scale-and-scope effect is not new. The idea of complementarities was proposed by Milgrom and Roberts [53]. They posited that in addition to *fit* among firm strategy, structure and processes, complementarities can also be relevant for higher productivity gains and optimization of resources. This is similar to the role of combined scale-and-scope effects in operations management. However, this notion has not been applied in context of regional economics and agglomeration so far. It is only very recently that the co-agglomeration has been recognized as a source of externality benefits [24]. Wheeler [73] also says that scale externalities cannot be fully explained by thick labor markets and human capital externalities. Co-agglomeration externalities in collocated IT industries are relevant for both the developed and developing contexts. Kratke [45] noted the changing nature of European cities with knowledge-intensive industries concentrating in urban agglomerations. We provide an empirical basis for the U.S. context. Tan and Leewongcharoen [68] emphasized the importance of location for growth of IT industries in developing countries. Kauffman and Kumar [44] discussed the combined scale-and-scope effects for IT industry growth in India.

The combined scale-and-scope effect may occur between industries due to several reasons. Ellison et al. [24] found evidence of labor pooling and knowledge spillovers between co-agglomerated industries. Other reasons may include trade relationships, process and knowledge domain similarities. With this synergy between some IT industries and the effect they may have on each other's growth, and our illustration of a methodology to measure this synergy, we do not claim to provide a complete account of combined scale-and-scope externalities that exist between co-agglomerated industries. There are several confounding factors which make such accurate assessment difficult. For example, the overall externalities results in the U.S. also may be downward-biased because of the dotcom bubble and offshoring, two shocks with constraining effects on IT industry growth. There may be other agglomeration-specific characteristics which we did not account for in our estimation, like time-distance from markets [37], and university linkages [74] which affect the level of innovation in an agglomeration [31].

This study has important implications for economic development of a country. Devereux et al. [20] found that government subsidies and other incentives have only a small effect in attracting firms to specific geographical areas and it is other benefits which determine firms' decisions to locate. The government policies should leverage the natural preferences of firms in determining locations. Though many countries have set up technology parks, not all have been successful [40]. Our study should encourage government and business agencies and staff (like managers of IT parks) involved in promoting IT industrial development to leverage the synergies between different IT industries to promote successful IT parks, and economic and social development [65]. Similar insights also may be useful in informing business managers in their choices of where to locate.

6. CONCLUSION AND LIMITATIONS

The empirical findings extend our understanding of the nature of the influences which different IT industries have on one another. Our conceptualization of the combined scale-and-scope effects provides an extension to the existing understanding of the MAR and Jacobs externalities. Our theoretical interpretation offers insights about how one IT industry influences growth of others in an agglomeration. Scale and scope economies have implications for firm performance [50]. Our work provides senior managers with some guidance about selecting locations for new IT firms.

We next address limitations of the approach. The model we used to analyze growth in industry accounts only for labor and not for capital. So it may not be able to capture the impacts of labor-saving technological innovations nor those which result in further accumulation of physical capital. Further, we used the *political boundaries of counties* as the boundaries of the agglomerations. However, since industry agglomerations are economic rather than political, we expect there to be *cross-county spatial interdependencies* which needs to be accounted for [47]. Another issue is the possibility of bias in our results due to self-selection. High-growth firms tend to seek locations which favor high growth. While it may be difficult to totally do away with the self-selection bias, using a fixed effects panel data model helps to controls for it. Notwithstanding the limitations, this study provides insights into the nature and sources of co-agglomeration of IT industries which can be exploited by regional planners for economic and social development.

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Table 4. Scale, Scope and Combined Scale-and-Scope Externalities

EXTERNALITY	THREE YEARS: 2001-2004 FGLS	THREE YEARS: 2001-2004 SUR	FOUR YEARS: 2000-2004 FGLS	FOUR YEARS: 2000-2004 SUR	SIX YEARS: 1998-2004 FGLS	SIX YEARS: 1998-2004 SUR
			***Computer and Peripheral Equipment Manufacturing* (1)**			
SCALE						$COMPTN_1$ (-)**
CSS	$SPCLN_4$ (-)***	$SPCLN_4$ (-)***	$SPCLN_4$ (-)*		$SPCLN_4$ (-)***	$SPCLN_4$ (-)***
R^2	38.5%	42.2%	36.1%	39.5%	26.8%	31.5%
Pr > F	0.001	0.001	0.002	0.002	0.022	0.001
			***Semiconductor and Other Electronic Components Manufacturing* (2)**			
SCALE	$SPCLN_2$ (-)* $COMPTN_2$ (-)*		$SPCLN_2$ (-)** $COMPTN_2$ (-)**		$SPCLN_2$ (-)** $COMPTN_2$ (-)***	$COMPTN_2$ (-) ***
SCOPE	*DIVERSITY* (-)**					
CSS	$SPCLN_1$ (+)* $SPCLN_1 \cdot SPCLN_4$ (-)** $SPCLN_2 \cdot SPCLN_4$ (+)**	$SPCLN_1$ (+)*** $SPCLN_1 \cdot SPCLN_4$ (-)*	$SPCLN_1$ (+)* $SPCLN_1 \cdot SPCLN_4$ (-)** $SPCLN_2 \cdot SPCLN_4$ (+)**	$SPCLN_1$ (+)*** $SPCLN_1 \cdot SPCLN_4$ (-)*		$SPCLN_1$ (+)** $SPCLN_1 \cdot SPCLN_4$ (-)** $SPCLN_2 \cdot SPCLN_3$ (-)** $SPCLN_2 \cdot SPCLN_4$ (+)**
R^2	17.4%	36.6%	19.1%	39.9%	15.3%	48.7%
Pr > F	0.001	0.001	0.001	0.001	0.001	0.001
			***Software Publishing* (3)**			
SCALE	$COMPTN_3$ (-)***	$COMPTN_3$ (-)***	$COMPTN_3$ (-)***	$COMPTN_3$ (-)***	$COMPTN_3$ (-)***	$COMPTN_3$ (-)***
SCOPE	*DIVERSITY* (-)**		*DIVERSITY* (-)**			
CSS	$SPCLN_1$_SQ (-)***		$SPCLN_1$_SQ (-)***		$SPCLN_2$_SQ (-)***	
R^2	24.7%	43.1%	20.5%	37.0%	29.1%	37.1%
Pr > F	0.001	0.001	0.001	0.001	0.001	0.001
			***Computer Systems Design and Related Services* (4)**			
SCALE	$COMPTN_4$(-)**		$SPCLN_4$(+)* $COMPTN_4$(-)**		$SPCLN_4$(+)**	
SCOPE	*DIVERSITY*(-)**	*DIVERSITY*(-)**	*DIVERSITY*(-)**	*DIVERSITY*(-)**	*DIVERSITY* (-)**	
CSS	$SPCLN_1$_SQ (+)*** $SPCLN_2 \cdot SPCLN_4$ (+)*	$SPCLN_2 \cdot SPCLN_4$ (+)*	$SPCLN_2$_SQ (-)** $SPCLN_3$_SQ (+)** $SPCLN_1 \cdot SPCLN_2$ (+)** $SPCLN_1 \cdot SPCLN_4$ (+)** $SPCLN_2 \cdot SPCLN_4$ (+)** $SPCLN_3 \cdot SPCLN_4$ (-)**	$SPCLN_1 \cdot SPCLN_4$ (-)** $SPCLN_2 \cdot SPCLN_3$ (-)* $SPCLN_2 \cdot SPCLN_4$ (+)**	$SPCLN_3$_SQ (+)* $SPCLN_3 \cdot SPCLN_4$ (-)**	
R^2	12.8%	33.9%	15.7%	34.6%	0.12.4%	22.7%
Pr > F	0.001	0.001	0.001	0.110	0.001	0.642

Notes. CSS: Combined scale-and-scope Effect. Only significant coefficients are presented. Control variables have been omitted for brevity. The abbreviation "SQ" for a variable indicates the square. Model for each IT industry is as shown in §4.1. Signif.: * $p < .10$, ** $p < .05$, *** $p < .01$.