THE SPATIAL EXTENT OF AGGLOMERATION ECONOMIES:

EVIDENCE FROM THREE U.S. MANUFACTURING INDUSTRIES

by

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Abstract

The spatial extent of localized agglomeration economies constitutes one of the central current questions in regional science. It is crucial for understanding firm location decisions and for assessing the influence of proximity in shaping spatial patterns of economic activity, yet clear-cut answers are difficult to come by. Theoretical work often fails to define or specify the spatial dimension of agglomeration phenomena. Existing empirical evidence is far from consistent. Most sources of data on economic performance do not supply micro-level information containing usable geographic locations.

This paper provides evidence of the distances across which distinct sources of agglomeration economies generate benefits for plants belonging to three manufacturing industries in the United States. Confidential data from the Longitudinal Research Database of the United States Census Bureau are used to estimate cross-sectional production function systems at the establishment level for three contrasting industries in three different years. Along with relevant establishment, industry, and regional characteristics, the production functions include variables that indicate the local availability of potential labor and supply pools and knowledge spillovers. Information on individual plant locations at the county scale permits spatial differentiation of the agglomeration variables within geographic regions. Multiple distance decay profiles are investigated in order to explore how modifying the operationalization of proximity affects indicated patterns of agglomeration externalities and interfirm interactions. The results imply that industry characteristics are at least as important as the type of externality mechanism in determining the spatial pattern of agglomeration benefits. The research methods borrow from earlier work by the author that examines the relationships between regional industrial structure and manufacturing production.

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INTRODUCTION

In a 2005 article assessing the state of agglomeration research, McCann and Shefer identify the spatial extent of localized agglomeration externalities as one of seven questions central to the current development of economic geography and regional science. Although theoretical arguments recognize geographic proximity as a requirement for gaining advantage from agglomeration, including benefiting from the Marshallian externalities of knowledge and information spillovers, labor pooling, and specialized inputs to production, different bodies of work presume dissimilar scales at which such advantages accrue to firms. For instance, the new economic geography literature tends to assume that the city is the critical geographic territory, whereas a number of researchers working in the economics and regional science traditions argue that "a regional hinterland extending well beyond the city may be a more appropriate area of advantage" (McCann and Shefer 2005, p. 304). Some scholarly literatures, including much of the theoretical work surrounding the ideas of clusters, new industrial spaces, and innovative milieux, omit or avoid explicit consideration of the spatial extent of agglomeration all together.

There is value in furthering understanding not only of different categories of agglomeration advantages but also how they are restricted by or mediated by space. Such knowledge can inform the continuing development of agglomeration theory and related literatures that depend on agglomeration mechanisms, such as new economic geography and regional innovation systems, that are vulnerable to criticisms of being divorced or too distant from real-world phenomena (McCann 2007; Martin 2010). Evidence supports the contention that spatial proximity remains important for firm location decisions and for the realization of regional advantage despite diminishing transportation and communication costs and increasingly globalized interactions (Arauzo-Carod *et al.* 2010; Lehto *et al.* 2011). The relationship between the type of externality and the spatial pattern of available benefits, however, may depend in a complex manner on industry and regional characteristics. Intelligence regarding the mechanisms and spatial scope of agglomeration is crucial for translating empirical research into practical guidance for policy and public decision-making. The process of choosing among possible interventions into regional economies to accomplish economic growth and development goals calls for awareness of the types of agglomeration benefits and an understanding of the physical locales where they are likely to be realized.

This paper aims to address part of the knowledge gap described above by providing empirical evidence regarding agglomeration economy benefits and their spatial characteristics, and by answering the question of whether the spatial patterns of agglomeration advantages are determined by the agglomeration mechanism or by industry characteristics. The study examines establishments located in the continental United States that are classified within three manufacturing industries. Cross-sectional production function systems are estimated for three Economic Census years using confidential data from the *Longitudinal Research Database* of the United States Census Bureau. Multiple agglomeration variables included in the production functions are constructed using county-level plant locations to incorporate spatial variation. Several distance decay profiles are tested empirically in order to help determine the spatial patterns of likely agglomeration externalities. These data and the approach offer several advantages: the coverage of the study industries is nearly complete within the United States, multiple sources of agglomeration benefits are distinguished and analyzed, and the spatial differentiation incorporated into the agglomeration measures presents a direct means of evaluating the influence of proximity at the intraregional scale.

The organization of the paper is as follows. The next section describes some of the difficulties involved in assessing the spatial extent of agglomeration economies and summarizes the findings of selected empirical research that addresses the question. Following descriptions of the methodology, data sources, variable construction, and sample characteristics, the empirical results are presented, first pertaining to a default set of spatial decay profiles and then obtained through modifying the defining parameters of the spatially variant agglomeration measures. A brief summary concludes.

PREVIOUS WORK

The body of empirical research on agglomeration economies is extensive, and attention to the subject increased substantially during the past fifteen years. Yet several important questions remain unresolved, such as the precise mechanisms through which knowledge spillovers or transmissions occur and the distinctive impacts of different kinds of agglomeration externalities. For background on the development and current state of agglomeration research, please refer to the reviews by Feser (1998), Rosenthal and Strange (2004), and Puga (2010).

Most empirical studies of agglomeration economies treat spatial issues as secondary, placing more emphasis on first demonstrating the significance of agglomeration externalities and second assessing the relative importance of multiple sources of agglomeration benefits. This approach certainly is understandable, given the persistence of debates over these existential questions and the continual accumulation of conflicting evidence regarding the relative importance of different types of agglomeration externalities (Strange 2009; Puga 2010). In fact, the research described here is no exception: this study is one component of a larger effort that investigates a wider set of relationships among agglomeration, regional industrial structure, and productivity (see, for example, Drucker 2011; Drucker and Feser 2012). Complicating matters, the spatial distribution of agglomeration benefits may not be consistent across different industries or sources of agglomeration. In other words, the mechanisms by which spatial co-location yields benefits—pooled labor markets, spillovers of knowledge, etc.—correspond to distinct types economic advantages that may be differentially influenced by local and regional characteristics and benefit production unequally across various industries.

Choices pertaining to data and methods are consequential in examining agglomeration externalities. Agglomeration cannot be measured directly, but is standardly estimated in terms of the potential for benefits based on observable characteristics (Richardson 1974). Many data sources otherwise useful for examining agglomeration do not provide explicit spatial definition, or contain spatial information at too coarse of a scale to be helpful. Specific economic and geographical settings as well as methodological strategies circumscribe empirical results and lead to disparate or conflicting results.

Table 1 summarizes the findings of a number of empirical studies conducted within the last decade or so that consider the spatial aspect of agglomeration. The listing is not exhaustive, but even so serves to illustrate the variety of settings, designs, and data sources that lead to a confusing array of conclusions. Some research finds that externalities exist primarily in a narrow band surrounding a spillover generator, dissipating rapidly with distance and dropping below significant levels at five kilometers or less. Other studies indicate that agglomeration benefits are substantial at distances of 100 miles or more (and past 800 kilometers for the influence of Canadian urban agglomerations, according to Partridge *et al.* 2007). The types of agglomeration considered include labor pooling, human capital development, knowledge spillovers from particular sources such as universities or the conduct of research and development, and

generalized localization or urbanization benefits. Some researchers investigate agglomeration economies within a productivity framework (Lehto 2007); others use employment growth (Hoogstra and van Dijk 2004; van Soest *et al.* 2006), new firm or establishment births (Rosenthal and Strange 2003; van Soest *et al.* 2006; Rosenthal and Strange 2010; Arauzo-Carod and Manjon-Antolin forthcoming), new firm employment (Rosenthal and Strange 2003; 2010), new firm survival (Renski 2011), prevailing wages (Fu 2007; Rosenthal and Strange 2008), or patents (Audretsch *et al.* forthcoming) to uncover agglomeration effects. Several European and North American countries are represented. The methods diverge, from case control design (e.g., Aharonson *et al.* 2007) to counting outcomes such as patents, firms, or research grants (e.g., Wallsten 2001; Rosenthal and Strange 2003; Audretsch *et al.* forthcoming) to observing new firm survival rates (e.g., Renski 2011) to estimating production functions in a manner similar to the approach taken in this study (e.g., Baldwin *et al.* 2008; Graham 2009).

It is difficult to find consistent patterns in Table 1 relating the features of the data and methodology to the spatial patterns revealed. At a more detailed level, however, two working hypotheses are suggested by agglomeration theory. First, distance may be more of an impediment to the realization of agglomeration benefits in those industries in which time plays a crucial role. Firms that rely on rapid innovation, customization, or just-in-time production may have less flexibility to maintain relationships or gain advantages from opportunities that exist across sizable distances. Second, agglomeration externalities for which the transmission mechanism necessitates less frequent face-to-face interactions should operate across greater distances. Therefore, of Marshall's three externality categories, advantages from labor pooling may diminish more rapidly with distance than those from knowledge spillovers, with the benefits from localized availability of specialized inputs depending on the particular input and the production technology.

Prior to the mid 1990s, a substantial quantity of empirical work investigated the questions surrounding agglomeration economies using production functions with aggregate regions as the unit of analysis (see the discussions in Eberts and McMillen 1999; Rosenthal and Strange 2004). These studies faced severe methodological obstacles, in particular aggregation bias and the lack of capital input data at the regional scale. Although they tended to find substantial and positive influences of agglomeration on productivity, the results exhibited wide variation and low

Table 1. Summary of Selected Studies of Spatial Extent of Agglomeration Externalities.

Author(s) and Year	**Type of Agglomeration**	**Location and Sample**	**Finding on Spatial Extent**
Aharonson *et al.* 2007	spillovers from universities and R&D	Canada, biotechnology	within 0.5 km (R&D), within 10 km (universities)
Arauzo-Carod and Manjon-Antolin *forthcoming*	urbanization	Spain, new firms	within 60 km
Audretsch *et al.* *forthcoming*	university spillovers (measured by patents)	Germany, high-tech startups	patents decrease with distance from nearest university
Baldwin *et al.* 2008	localization	Canada	within 5 km
Barrios *et al.* 2008	R&D spillovers, labor pooling	Ireland	within 10-20 km (R&D), up to 50km or more (labor)
Desmet and Fafchamps 2005	localization, urbanization	US counties	up to 20 km (service sectors), up to 70 km (other sectors)
Feser 2002	labor pooling, supply pooling, knowledge spillovers	US, plants in two manufacturing industries	up to 50 miles, steeper decays for labor pooling, manufactured inputs
Fu 2007	human capital	Boston region	steep decay beyond 3 miles
Graham 2009	localization, urbanization	United Kingdom	within 10 km
Hanink 2006	localization, urbanization	US counties in New England	within counties
Hoogstra and van Dijk 2004	localization, diversity, other types	Netherlands	within 10 km (localization), within 5 km (others)
Lehto 2007	R&D spillovers	Finland	greater impacts of external R&D with proximity
Partridge *et al.* 2007	urbanization	Canada	up to 800 km or more
Renski 2011	urbanization, localization, diversity	US	up to 160 km, varies by industry sector and agglomeration type
Rosenthal and Strange 2003	localization	US, six industries	within 15 miles, strong decay after 1-2 miles
Rosenthal and Strange 2008	human capital spillovers	US	strongest within 5 miles, persistent at 50 or more miles
Rosenthal and Strange 2010	localization, urbanization	US	strongest within 5 miles, significant up to 100 miles
van Soest *et al.* 2006	localization, competition, diversity	Netherlands	strongest within 6-digit zip codes

Wallsten 2001	localization	US	within 5 miles
Woodward *et al.* 2006	university spillovers	US	within 145 miles

reliability (Gerking 1994; Moomaw 1998). During the last 15 years, increasing availability of micro-level data has made establishment-level production functions the favored approach. At the scale of individual plants, aggregation bias is not an issue and the options for measuring the capital input to production are superior. Micro-level production function studies have also found substantial agglomeration influences on productivity, with variation in results that is attributable to distinctions among agglomeration sources, industries, and establishment sizes rather than methodological impediments (e.g., Malmberg *et al.* 2000; Feser 2001; 2002; Rigby and Essletzbichler 2002b; Henderson 2003; Drucker and Feser 2012).

METHODOLOGY, DATA, AND VARIABLES

Production Function

This study evaluates agglomeration economies by examining the effects of several potential sources of agglomeration benefits on plant-level productivity. The production function is specified in translog form:

$$\begin{aligned}\ln Q = \alpha_0 &+ \sum_i \alpha_i \ln X_i + \frac{1}{2}\sum_i \sum_j \beta_{ij} (\ln X_i \ln X_j) \\ &+ \sum_k \gamma_k \ln Z_k + \sum_i \sum_k \mathrm{I}(i,k)\lambda_{ik} \ln X_i \ln Z_k + \sum_k \sum_l \mathrm{I}(k,l)\lambda_{kl} \ln Z_k \ln Z_l\end{aligned} \tag{1}$$

where Q is establishment output; X represents four conventional inputs (capital, labor, energy, and materials); Z is a vector of regional and industrial characteristics that includes measures of agglomeration economy sources; i and j index the inputs in X; and k and l index the components of Z. The translog form avoids imposing strong *a priori* assumptions such as constant returns to scale. The two indicator functions permit selective inclusion of interaction terms: the first allows the variables in Z to enter the production function in factor-augmenting form; the second allows for interactions among agglomeration and other measured regional and industrial features.

Following the inverse demand function methodology of Kim (1992), cost share equations derived from first-order profit maximization conditions are estimated jointly with the production function in order to improve efficiency. The system is estimated through iterated nonlinear seemingly unrelated regression. All non-dummy variables are mean-centered to enter the

production function so that the estimated parameters refer to the direct effects at the sample means of the other variables rather than at their zero points (Aiken and West 1991). Variables not measured as percentages or ratios are transformed with natural logarithms; the coefficient estimates are interpreted as elasticities at the sample means. A more detailed account of the methodology is available in Drucker and Feser (2007) or Drucker and Feser (2012).

Plant-Level Data

The *Longitudinal Research Database* (LRD) of the United States Census Bureau provides the plant-level data used to estimate the production function systems. The LRD is compiled from confidential establishment-level records collected for the *Census of Manufactures* in years ending in -2 or -7 and for the *Annual Survey of Manufactures* in other years. The dataset contains establishment locations by county, primary industry classification, and other establishment characteristics including employment and value of shipments. [See McGuckin (1990) for database construction and content details.]

Although the LRD includes entries for all U.S. establishments reporting under a manufacturing industry code, the coverage of most data items is incomplete for small establishments in non-census years.[1] Only census year data are used so as to maintain an accurate balance among establishment sizes. Establishments exempt from complete filing requirements (those with five or fewer employees for most manufacturing industries in most years) are excluded since they do not report directly on production inputs. The production system is estimated cross-sectionally by industry for each of the three most recent census years available: 1992, 1997, and 2002.

Because the original source of the LRD is confidential records, the Census Bureau strictly regulates the use of the dataset and any subsequent release of descriptive statistics and analytical results. All of the information presented has been reviewed by Census Bureau staff to ensure confidentiality. Additional restrictions to protect confidentiality and disclosure screening requirements limit the types and quantity of information that are permitted to be extracted.

[1] The ASM is a five-year panel sample of plants with rotating membership. Only large plants (normally those with at least 250 employees) are included with certainty. The remainder of the sample is selected randomly. Sample weights support imputations to industries at the national scale or to the manufacturing sector within particular regions, but not to industries within regions. In any given year the ASM includes less than 20 percent of United States manufacturing plants. (Despite its name, the LRD is not a longitudinal database at the establishment level.)

Industries

The study examines three manufacturing industries: plastics and rubber (SIC 30), metalworking machinery (SIC 354), and measuring and controlling devices (SIC 382).[2,3] These industries are selected to satisfy multiple criteria. Each industry contains a sufficient number of establishments spread across enough regions to offer adequate variation in potential agglomeration economies and ample observations to support the translog estimation system. Plants in these industries are flexible in location choice and relatively homogeneous in production technology. The selection contrasts two traditional industries producing standardized products in a capital-intensive manner with the more technology-intensive industry of measuring devices.

Regions

The geographic regions are 1990 Labor Market Areas (LMAs) as defined by the United States Department of Agriculture (2003). The LMAs are constructed by amalgamating individual counties in order to approximate the boundaries of functional economic areas, covering the entire United States. The study omits Alaska and Hawaii due to their relatively isolated locations, and also excludes the three LMAs that correspond to the urban centers of New York, Los Angeles, and Chicago as outliers due to those regions' size, density, and volume of international linkages. Regions that house fewer than twelve firms in an industry are excluded from the analysis (of that industry only) in order to preserve the meaning of the regional industrial concentration control variable.[4]

Agglomeration

Five variables indicating the potential for local agglomeration economies are included in the production function. These agglomeration measures combine LRD data with publicly available information, and are conceptually and computationally similar to measures employed successfully in recent agglomeration research (Feldman and Audretsch 1999; Drennan *et al.*

[2] The number of industries available for study is limited by Census restrictions on data extraction and screening procedure burdens.
[3] "Measuring and controlling devices" is shortened to "measuring devices" for brevity.
[4] Sensitivity checks demonstrate that varying the minimum number of firms in the regional industry from as few as six to as many as fifty alters the strength of the estimations but not the qualitative interpretations of the results obtained.

2002; Feser 2002; Rigby and Essletzbichler 2002a; Renski and Feser 2004; Koo 2005a; Renski 2006).

For all but one of the five measures, agglomeration potential is calculated at the establishment scale incorporating intraregional spatial attenuation with distance. The LRD information on establishment locations by county allows an enormous improvement over regionally-invariant agglomeration measures. Exponential distance decays commonly are modeled by applying a weight factor of $d^{-\alpha}$, where d is distance and α controls the rapidity of the attenuation with distance (see Figure 1) (Anselin 2002; Hu and Pooler 2002). The distance decay is truncated with an absolute cutoff distance D_{max}. The aim of the study to investigate different spatial patterns of agglomeration influence is accomplished by empirically testing combinations of α (distance decay) and D_{max} (cutoff distance).

Labor pooling agglomeration potential is measured as an establishment's access workers with skills that roughly match the industry's expected occupational requirements:

(2) $$AL_{kx} = \sum_{c} \left(\frac{O_{cx}}{O_{cT}} d_{ck}^{-\alpha} \right)$$

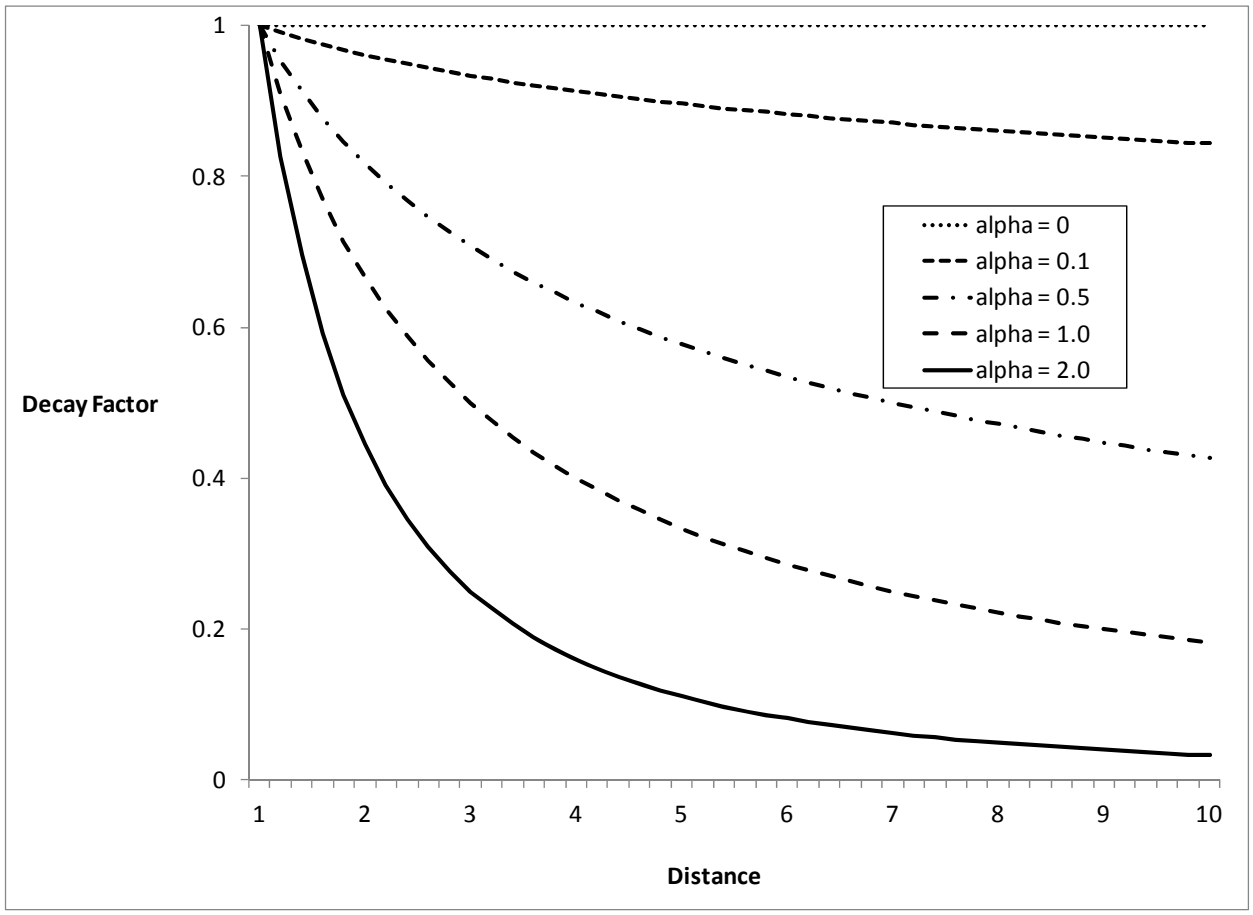
where x is the study industry, c indexes counties, k is the county of the target establishment, O_{cx} is county c's residential workforce employed in the top 15 occupations employed by industry x nationally (identified from the Bureau of Labor Statistics national staffing matrix), O_{cT} is county c's total residential workforce, and d_{ck} is the distance between county c and the county of the target establishment, measured as the great circle distance between county centroids. Values of O_c and O_{cT} are taken from the 1990 and 2000 Census Equal Employment Opportunity tabulations.

Potential supply pools of manufactured inputs and producer services are calculated by weighting the local presence of supplier industries by the importance of each industry as a supplier to the study industry at the national level. Manufacturing input supply pooling agglomeration is:

(3) $$AI_{kx} = \sum_{c} \left(\left(\sum_{m} \frac{E_{cm} P_{xm}}{P_{xM}} \right) \cdot d_{ck}^{-\alpha} \right)$$

where m indexes manufacturing industries, x signifies the study industry, c indexes counties, k is the county of the target establishment, E_{cm} is county c's employment in industry m, P_{xm} is the dollar amount that the study industry purchases nationally from supplier industry m, P_{xM} is the

Figure 1. Example Distance Decay Profiles.



study industry's total national purchases from the manufacturing sector, and d_{ck} is the same as for labor pooling. Producer services pooling agglomeration has nearly the same formula except that purchases and local employment are totaled for suppliers of producer services:

(4) $$AS_{kx} = \sum_{c} \left(\left(\sum_{s} \frac{E_{cs} P_{xs}}{P_{xS}} \right) \cdot d_{ck}^{-\alpha} \right)$$

where s indexes producer services industries and P_{xS} is the study industry's total national purchases of producer services. Purchase amounts are derived from the Make and Use tables of the *Benchmark Input-Output Accounts* from the Bureau of Economic Analysis. E_{cm} and E_{cs} are tabulated from the *Longitudinal Business Database*, a confidential establishment-level Census dataset that covers most economic sectors but does not contain full input and output information.

Knowledge spillovers are typically proxied by input measures such as university research expenditures and the density of employment of scientists and engineers, or outcome measures such as patents or new inventions (Jaffe *et al.* 1993; Fritsch and Lukas 1999; Fritsch and Meschede 2001; Kirchhoff *et al.* 2002; Moreno *et al.* 2006; Sonn and Storper 2008; Ponds *et al.* 2010; Crespi *et al.* 2011; Audretsch *et al.* forthcoming). For this study, the relevant construct is access to potential sources of knowledge, rather than aggregate outcomes. The potential labor pooling measure (*AL*) already accounts for the concentration of scientists and engineers. Two variables indicate different types of knowledge spillovers. The first gauges regional access to relevant basic research and knowledge:

(5) $$AR_{kx} = \sum_{c} \left(\left(\sum_{f} R_{cf} \right) \cdot d_{ck}^{-\alpha} \right)$$

where f indexes industry-relevant academic fields, R_{cf} is the total amount of research expenditures in academic field f during the previous five years at research universities located in county c, and the other variables are as in equations 2, 3, and 4. The cutoff distances tested are greater than for the other agglomeration variables because university-industry interactions in general need occur with less frequency and convenience than labor and supply interactions to have significant impacts upon firm practices (Matkin 1990; Tornatzky and Fleischer 1990). The academic fields relevant to each industry are modified from Cohen *et al*. (2002). The National Science Foundation's CASPAR database provides the annual university research expenditures information.

Second, patenting provides an indication of the extent of private sector research activity and regional innovative culture. Many studies acknowledge faults with patents as a proxy for innovative activity, yet empirical research suggests that patents are related to the market value of knowledge, and in any case there are few viable alternatives (Jaffe 1989; Jaffe *et al.* 1993; Henderson *et al.* 1998; Acs *et al.* 2002; Agrawal and Cockburn 2003; Sampat *et al.* 2003; Ketelhohn 2006). The patent measure (*AP*) weights the volume of patents in each technology classification by the relative importance of those technology categories to the target industry:

(6) $$AP_{rx} = \sum_{g \in K} \left(\frac{PAT_{gr}}{POP_{r}} N_{gx} \right)$$

where g indexes patent technology classifications, r signifies the region, x represents the study industry, K is the set of patent technology classifications relevant to the study industry (both

directly and via cross-industry spillovers), PAT_{gr} is the number of utility patents granted within region r in the last five years in patent technology class g (from the CASSIS bibliographic system of the U.S. Patent and Trademark Office), POP_r is the regional residential population, and N_{gx} is a measure of relevance derived from tabulations of patent citations (Koo 2005b). Unlike the other agglomeration variables, *AP* incorporates geography solely in terms of regional boundaries; more precise geographic assignation of patents using the inventor location information is highly problematic (Jaffe *et al.* 1993; Feldman 1999). Industry-relevant patent technology classifications are identified from the USPTO technology-industry match and a technology flow matrix developed by Koo (2005b).

Additional Independent Variables

Because this paper focuses on the spatial extent of agglomeration externalities, the other model variables are described only cursorily. Appendix A lists all of the variables (Table A-1) along with their data sources and construction, and Drucker and Feser (2012) provides descriptive information and estimation results for the full production model.

Establishment size is captured by two dummy variables. The first identifies plants that belong to the five largest firms in the regional industry; the other signifies establishments that are part of relatively small firms, those reporting less than one tenth the shipment value of the fifth largest firm.[5] Industrial concentration at the regional scale, hypothesized to restrict the ability of smaller firms to benefit from locally available agglomeration economies, is measured with a five-firm concentration ratio based on shipment value.[6,7] Dummy variables for Census Regions proxy different macro-regional levels of development and macroeconomic conditions. Regional unemployment rates and median household income levels reflect local economic conditions, and population density helps control for regional size, level of resources, and the absolute dimension of potential agglomeration economies, as well as urban congestion and other agglomeration diseconomies. A regional Herfindahl-Hirschman index calculated across four-digit SIC

[5] Alternative plant size measures based on absolute size (number of employees) were also tested.
[6] For aggregating establishments to firms, industries are defined at the most detailed classification level available in the LRD: four-digit SIC or six-digit NAICS industry categories, assigned according to primary production activity. For multi-unit firms, establishments are aggregated by combining plants in the same industry and region. Establishments belonging to multi-unit firms that are located within different regions or that are classified into different industries remain separate "firms". Establishments exempt from full reporting requirements are included here since all establishments report shipment values.
[7] Drucker and Feser 2007 examine additional measures; the results are qualitatively similar to those presented here.

industries measures regional industrial diversity (inversely), controlling for "Jacobs externalities" that pertain within regions across different industries (Glaeser *et al.* 1992). Changes in regional industrial concentration and industrial diversity from twenty years prior to the model year distinguish cumulative or persistent structural effects.

Endogeneity

Endogeneity is a concern in empirical agglomeration research. Some scholars contend that the firms that are the most productive for unobserved reasons may be those that are best at identifying receptive, productivity-enhancing locations. Such location selectivity would suggest that measures of agglomeration are endogenous in the production function, determined jointly with production (Hanson 2001; Henderson 2003; Graham and Kim 2008). This concern is a particular case within the general issue of possible endogeneity in firm input selection.

Two statistical approaches are commonly adopted in the literature to address endogeneity: instrumentation and fixed effects (e.g., see Henderson 2003). Unfortunately, neither strategy is appropriate here. Input prices, the standard choice of instruments, are not applicable to untraded agglomeration economies (Ackerberg *et al.* 2006). There are no effective instruments available for specific sources of agglomeration benefits at the regional and intraregional scales. Time fixed effects require balanced panel datasets, which for this study would require excluding plants that do not appear in each study year of the LRD and thus severely curtailing spatial and firm size variation. Location fixed effects, on the other hand, remove the geographic variation at the heart of this research.

Two considerations may moderate the validity threat posed by potential endogeneity to this study. First, to some degree the research design constrains the hazard. The exogeneity of agglomeration advantages is a much more reasonable assumption for individual establishments than for aggregate industries. Moreover, the production function contains establishment-specific variables for multiple sources of agglomeration economies, thereby measuring directly some of the relevant plant-level characteristics that were unobservable factors in previous research. Second, a variety of recent empirical analyses demonstrate that endogeneity distortions are typically small and are as likely to understate as to exaggerate the influence of agglomeration (Henderson 2003; Rice *et al.* 2006; Ellison *et al.* 2007; Koo and Lall 2007; Puga *et al.* 2007).

Nevertheless, the possibility of bias is present and should be considered in interpreting the empirical findings.

DESCRIPTIVE INFORMATION

Table 2 reports the total number of establishments included in the study by industry along with the count of those omitted from analysis. Most of the excluded plants are small establishments that are exempt from complete filing requirements. Increases in mean sizes over time reflect consolidation that has accompanied declining employment in the manufacturing sector. Each of the industry-year sets of plants is skewed by size: most plants have input and output quantities below the mean and the dispersion is greater (has a longer tail) at the large end. Most of the plants are located in urban areas, due to the geographical distribution of the industries and also the omission of regions with few establishments.

Descriptive statistics and correlations among the agglomeration variables are presented in Tables 3 and 4 using initial agglomeration variable parameters of $\alpha = 1.0$ (a relatively steep decay), D_{max} = 75 miles for labor pooling (*AL*), manufactured inputs (*AI*), and producer services (*AS*), and D_{max} = 200 miles for university research (*AR*). (Recall that patenting, *AP*, does not vary intraregionally.) Several facts merit mention. Establishments in the plastics and rubber industry have the lowest average values for potential regional labor pooling; however, because the labor pooling measure is based on the particular occupations most employed within each industry, it is not precisely comparable across industries. Measuring and controlling device plants tend to be located in highly innovative regions, with substantially larger potential

Table 2. Samples.

Industry	*Plastics and Rubber*			*Metalworking Machinery*			*Measuring Devices*		
Year	1992	1997	2002	1992	1997	2002	1992	1997	2002
Sample observations	6,747	8,000	6,546	5,189	5,490	4,161	1,384	1,540	1,201
Dropped observations	6,169	6,499	5,128	4,053	4,522	3,982	2,385	2,582	2,211
Percent retained in sample	52.2	55.2	56.1	56.1	54.8	51.1	36.7	37.4	35.2
Mean employment	78	82	91	33	38	36	97	94	111
Mean shipments	9,912	12,789	16,259	3,417	5,191	5,185	12,891	17,603	22,393
Percent with < 51 employees	59.8	58.1	54.3	85.9	83.5	83.7	64.0	62.9	59.8
Percent below mean employment	73.2	72.1	72.4	77.8	76.4	76.2	77.1	77.2	79.7
Percent below mean shipments	74.8	74.7	74.7	80.6	80.7	80.0	79.5	82.4	81.8

Note: Value of shipments reported in thousands of nominal dollars.

Table 3. Variable Descriptives.

Plastics and Rubber		*1992 (n=6,747)*			*1997 (n=8,000)*			*2002 (n=6,546)*		
Year		mean	std. dev.	%>mn.	mean	std. dev.	%>mn.	mean	std. dev.	%>mn.
Labor Pooling	AL	0.079	0.016	42.1	0.099	0.030	40.3	0.119	0.033	42.2
Manufactured Inputs	AI	561	751	34.8	342	437	33.5	301	415	30.9
Producer Services	AS	4,701	4,979	37.2	2,461	2,735	34.6	2,627	3,203	32.8
Research	AR	22,600	34,996	28.0	27,315	41,560	26.1	30,717	48,011	24.4
Patenting	AP	21.22	9.61	48.4	21.09	10.71	47.1	23.62	12.42	45.8
Industry Concentration	C	0.387	0.191	47.8	0.404	0.195	47.1	0.449	0.198	42.3
Metalworking Machinery		*1992 (n=6,747)*			*1997 (n=8,000)*			*2002 (n=6,546)*		
Year		mean	std. dev.	%>mn.	mean	std. dev.	%>mn.	mean	std. dev.	%>mn.
Labor Pooling	AL	0.121	0.016	41.5	0.149	0.018	49.9	0.126	0.025	51.8
Manufactured Inputs	AI	722	637	35.4	644	577	38.1	571	517	39.2
Producer Services	AS	4,386	4,199	36.4	1,973	2,044	34.8	2,068	2,358	33.1
Research	AR	28,966	58,476	22.3	39,650	74,452	21.6	47,170	87,304	20.3
Patenting	AP	18.37	6.78	48.2	18.52	8.31	46.3	21.02	10.07	48.9
Industry Concentration	C	0.413	0.196	47.0	0.436	0.209	48.4	0.453	0.201	42.2
Measuring Devices		*1992 (n=6,747)*			*1997 (n=8,000)*			*2002 (n=6,546)*		
Year		mean	std. dev.	%>mn.	mean	std. dev.	%>mn.	mean	std. dev.	%>mn.
Labor Pooling	AL	0.137	0.020	39.5	0.196	0.027	42.5	0.151	0.026	40.9
Manufactured Inputs	AI	1,728	2,167	25.2	2,374	4,113	18.3	2,051	3,194	22.9
Producer Services	AS	7,089	4,425	50.5	4,401	3,039	47.8	5,268	3,809	46.5
Research	AR	160,186	229,831	22.9	185,002	267,781	29.5	201,325	261,265	27.8
Patenting	AP	61.57	24.77	40.2	72.12	39.13	32.2	96.29	70.24	36.0
Industry Concentration	C	0.543	0.184	44.5	0.591	0.152	45.5	0.643	0.139	38.4

Note: Labor pooling, manufactured inputs, and producer services calculated with $\alpha = 1$ and $D_{max} = 75$ miles; research defined with $\alpha = 1$ and $D_{max} = 200$ miles.

spillovers from university research and an average regional patenting rate three to five times greater than for the other two study industries. The producer services variable drops markedly between 1992 and 1997, but this likely represents changed purchasing patterns and a shift in the input-output coding scheme in that period more than altered availability of producer services; cross-sectional comparisons should not be affected, and a modest increase follows from 1997 to 2002. The mean levels of industrial concentration reported in each industry rise consistently over the three study years, again likely the result of manufacturing-wide contraction and consolidation.

The five agglomeration measures are substantially positively correlated, as is typical in empirical studies of multiple sources of agglomeration economies (Breschi and Lissoni 2001; Renski 2006; Puga 2010). Nevertheless, the variables are sufficiently distinct to include together

Table 4. Variable Correlations.

Plastics and Rubber		1992					1997					2002				
		AL	AI	AS	AR	AP	AL	AI	AS	AR	AP	AL	AI	AS	AR	AP
Labor Pooling	AL															
Manufactured Inputs	AI	-0.087					-0.192					-0.233				
Producer Services	AS	-0.632	0.712				-0.598	0.778				-0.644	0.796			
Research	AR	-0.284	0.602	0.617			-0.294	0.615	0.587			-0.360	0.651	0.636		
Patenting	AP	-0.008	0.412	0.231	0.405		-0.004	0.385	0.285	0.424		-0.059	0.424	0.292	0.414	
Industry Concentration	C	0.155	-0.487	-0.423	-0.392	-0.543	0.113	-0.443	-0.439	-0.341	-0.484	0.196	-0.476	-0.452	-0.366	-0.513
Metalworking Machinery		1992					1997					2002				
		AL	AI	AS	AR	AP	AL	AI	AS	AR	AP	AL	AI	AS	AR	AP
Labor Pooling	AL															
Manufactured Inputs	AI	0.443					0.181					0.000				
Producer Services	AS	-0.005	0.745				-0.370	0.762				-0.517	0.763			
Research	AR	-0.255	0.383	0.575			-0.329	0.480	0.574			-0.381	0.490	0.571		
Patenting	AP	0.518	0.505	0.306	0.192		0.262	0.545	0.378	0.251		0.160	0.548	0.375	0.215	
Industry Concentration	C	-0.488	-0.493	-0.354	-0.034	-0.525	-0.320	-0.504	-0.342	-0.082	-0.598	-0.255	-0.534	-0.277	-0.108	-0.547
Measuring Devices		1992					1997					2002				
		AL	AI	AS	AR	AP	AL	AI	AS	AR	AP	AL	AI	AS	AR	AP
Labor Pooling	AL															
Manufactured Inputs	AI	0.606					0.654					0.582				
Producer Services	AS	0.166	0.684				0.207	0.658				0.107	0.689			
Research	AR	0.269	0.653	0.525			0.312	0.620	0.524			0.331	0.594	0.529		
Patenting	AP	0.532	0.523	0.125	0.394		0.575	0.553	0.099	0.401		0.662	0.571	0.155	0.444	
Industry Concentration	C	-0.293	-0.399	-0.287	-0.521	-0.537	-0.202	-0.278	-0.180	-0.472	-0.472	-0.051	-0.224	-0.206	-0.324	-0.357

Notes: Correlations measured with natural logarithms of all variables except for labor pooling and industry concentration. Labor pooling, manufactured inputs, and producer services calculated with $\alpha = 1$ and $D_{max} = 75$ miles; research defined with $\alpha = 1$ and $D_{max} = 200$ miles.

in the analysis. Agglomeration potentials tend to be negatively correlated with industry concentration, since larger and denser regions that provide more possibility for agglomeration externalities are less likely to be dominated by a single or a few plants in a given industry. Additional descriptive information is available in Drucker and Feser (2007).

EMPIRICAL RESULTS

The production function systems for each industry and year are re-estimated six times, varying the two flexible parameters that define the spatial decay of the measures of potential agglomeration externalities. Evaluating the results obtained from different combinations of α (the distance decay parameter) and D_{max} (the maximum cutoff distance) permits an empirical assessment of the spatial patterns of agglomeration benefits. Tables 5 through 7 show the full parameter estimates for the production function model using initial agglomeration variable parameters: $\alpha = 1.0$ (a relatively steep decay) for the measuring devices industry and $\alpha = 0.1$ (a much flatter decay) for the plastics and rubber and metalworking machinery industries; across all three industries $D_{max} = 75$ miles for labor pooling (*AL*), manufactured inputs (*AI*), and producer

services (*AS*), and D_{max} = 200 miles for university research (*AR*). (Patenting, *AP*, does not vary intraregionally.) Tables 8 through 10 contain the estimates coefficients for the agglomeration variables only, applying six spatial decay profiles (the default profile contained in Tables 5 through 7 and five additional profiles).[8,9]

Non-Agglomeration Variables

The production function models yield mainly the expected results for the variables other than agglomeration. The coefficients of the conventional inputs demonstrate that production is positively related to input quantities, and negative cross-products indicate input substitution. Firm size is important: plants in the largest firms enjoy a productivity advantage that ranges from 14 to 28 percent depending on the industry and year, and plants that are part of the smallest firms suffer a production disadvantage of similar magnitude. Greater concentration within regional industries substantially reduces plant productivity, with larger effects for metalworking machinery and measuring device establishments than for plastics and rubber manufacturers. Industrial diversity has a small but significant beneficial effect in the metalworking machinery and measuring devices industries, indicating Jacobs externality advantages from cross-industry spillovers. The more traditional, more mature plastics and rubber industry displays no such benefit. The effects of concentration and diversity are stable; the variables indicating change over time have negligible influences.

At the regional scale, population density has effects on productivity that are predominantly positive and significant but small in magnitude. Income tends to be positively related to productivity in the plastics and rubber industry, perhaps serving as an indicator for local workforce skills. Income is negatively related to productivity in the other industries, however; labor's average share of production cost is greater for metalworking machinery and measuring devices plants, so wage costs may outweigh skill advantages. The impacts of unemployment, industrial diversity, and the Census Region dummy variables vary across industries and years, suggesting that associations with plant-level production may be specific to the industry and/or the local economic circumstances.

[8] Many more parameter choices and permutations of decays and distance cutoffs were tested that span the spectrum from very narrow to quite broad patterns of spatial decay. These six profiles serve to illustrate the trends observed across the larger set of results.

[9] For the most part, the estimated coefficients of the other variables in the production model are only slightly altered from the figures reported in Tables 5 through 7 and so are not presented.

Table 5. Parameter estimates, plastics and rubber (SIC 30).

Year	1992			1997			2002		
Variable	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.
constant	8.278	0.011	0.00	8.436	0.011	0.00	8.788	0.012	0.00
ln K	0.130	0.001	0.00	0.168	0.001	0.00	0.198	0.001	0.00
ln L	0.334	0.002	0.00	0.308	0.001	0.00	0.298	0.002	0.00
ln E	0.027	0.000	0.00	0.023	0.000	0.00	0.022	0.000	0.00
ln M	0.447	0.002	0.00	0.443	0.002	0.00	0.418	0.002	0.00
$(\ln K)^2$	0.085	0.001	0.00	0.096	0.001	0.00	0.102	0.001	0.00
$(\ln L)^2$	0.142	0.002	0.00	0.138	0.001	0.00	0.119	0.001	0.00
$(\ln E)^2$	0.019	0.000	0.00	0.017	0.000	0.00	0.016	0.000	0.00
$(\ln M)^2$	0.172	0.001	0.00	0.179	0.001	0.00	0.157	0.001	0.00
ln K · ln L	-0.032	0.001	0.00	-0.033	0.001	0.00	-0.038	0.001	0.00
ln K · ln E	-0.003	0.000	0.00	-0.002	0.000	0.00	-0.003	0.000	0.00
ln K · ln M	-0.056	0.001	0.00	-0.067	0.001	0.00	-0.073	0.001	0.00
ln L · ln E	-0.005	0.000	0.00	-0.005	0.000	0.00	-0.003	0.000	0.00
ln L · ln M	-0.114	0.001	0.00	-0.108	0.001	0.00	-0.094	0.001	0.00
ln E · ln M	-0.012	0.000	0.00	-0.010	0.000	0.00	-0.011	0.000	0.00
C	-0.045	0.039	0.25	-0.051	0.033	0.12	-0.065	0.037	0.08
AL	0.900	0.593	0.13	0.040	0.324	0.90	0.686	0.344	0.05
ln AI	0.005	0.013	0.67	0.000	0.011	0.98	-0.011	0.013	0.41
ln AS	-0.005	0.012	0.66	0.000	0.012	0.97	0.016	0.013	0.22
ln AR	0.002	0.009	0.86	0.007	0.007	0.32	0.005	0.008	0.50
ln AP	0.003	0.012	0.81	0.020	0.010	0.04	0.021	0.011	0.07
C^2	-0.451	0.259	0.08	-0.301	0.215	0.16	-1.057	0.263	0.00
C · AL	0.372	2.754	0.89	-1.368	1.030	0.18	-0.850	1.283	0.51
C · ln AI	0.024	0.061	0.69	0.035	0.045	0.44	0.014	0.053	0.80
C · ln AS	-0.046	0.051	0.37	-0.044	0.043	0.30	-0.106	0.051	0.04
C · ln AR	0.039	0.037	0.29	0.041	0.028	0.14	0.033	0.035	0.34
C · ln AP	-0.061	0.045	0.18	-0.014	0.038	0.72	-0.123	0.040	0.00
C · ln K	0.021	0.004	0.00	0.006	0.003	0.07	0.012	0.005	0.01
C · ln L	0.027	0.008	0.00	-0.003	0.006	0.62	0.023	0.007	0.00
C · ln E	0.001	0.001	0.35	-0.002	0.001	0.01	0.001	0.001	0.46
C · ln M	0.035	0.008	0.00	-0.006	0.006	0.31	0.017	0.008	0.03
AL · ln K	-0.082	0.072	0.25	0.025	0.034	0.46	0.159	0.044	0.00
AL · ln L	0.056	0.152	0.71	-0.105	0.057	0.06	0.078	0.067	0.25
AL · ln E	-0.093	0.028	0.00	-0.070	0.009	0.00	-0.067	0.010	0.00
AL · ln M	0.083	0.165	0.61	0.119	0.062	0.06	0.380	0.073	0.00

Year	1992			1997			2002		
Variable	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.
ln AI · ln K	0.004	0.002	0.02	0.003	0.001	0.01	0.001	0.002	0.57
ln AI · ln L	0.000	0.003	0.97	0.000	0.002	0.88	-0.002	0.003	0.61
ln AI · ln E	0.001	0.001	0.11	0.000	0.000	0.67	0.000	0.000	0.36
ln AI · ln M	0.014	0.003	0.00	0.000	0.003	0.90	0.003	0.003	0.32
ln AS · ln K	-0.002	0.001	0.10	-0.004	0.001	0.01	0.001	0.002	0.68
ln AS · ln L	0.007	0.003	0.02	0.001	0.002	0.66	0.005	0.003	0.08
ln AS · ln E	0.001	0.001	0.06	0.000	0.000	0.57	0.000	0.000	0.30
ln AS · ln M	-0.007	0.003	0.02	-0.003	0.003	0.24	0.003	0.003	0.36
ln AR · ln K	-0.001	0.001	0.49	0.002	0.001	0.04	0.002	0.001	0.04
ln AR · ln L	0.003	0.002	0.13	0.003	0.001	0.01	0.003	0.002	0.08
ln AR · ln E	0.001	0.000	0.00	0.002	0.000	0.00	0.002	0.000	0.00
ln AR · ln M	-0.007	0.002	0.00	0.002	0.001	0.24	-0.001	0.002	0.50
ln AP · ln K	0.002	0.001	0.22	-0.003	0.001	0.01	0.000	0.002	0.99
ln AP · ln L	0.007	0.003	0.01	0.008	0.002	0.00	0.011	0.002	0.00
ln AP · ln E	0.000	0.000	0.57	0.000	0.000	0.33	0.001	0.000	0.03
ln AP · ln M	-0.007	0.003	0.01	-0.009	0.002	0.00	-0.004	0.003	0.10
D	0.141	0.013	0.00	0.149	0.012	0.00	0.192	0.013	0.00
S	-0.191	0.010	0.00	-0.174	0.009	0.00	-0.159	0.010	0.00
R1	-0.019	0.015	0.19	0.018	0.012	0.13	0.001	0.015	0.94
R2	-0.004	0.013	0.74	0.003	0.014	0.82	-0.013	0.016	0.39
R3	-0.023	0.017	0.19	-0.002	0.015	0.90	-0.018	0.020	0.35
ln POP	0.024	0.008	0.00	0.006	0.007	0.38	0.001	0.008	0.92
UE	-0.485	0.307	0.11	0.683	0.287	0.02	-0.251	0.487	0.61
ln INC	0.139	0.051	0.01	0.095	0.043	0.03	0.090	0.046	0.05
DV	1.609	1.112	0.15	-1.494	0.852	0.08	0.554	0.816	0.50
CH	-0.012	0.028	0.67	-0.002	0.026	0.94	-0.060	0.035	0.09
DVH	-0.148	0.961	0.88	-0.349	0.581	0.55	0.735	0.655	0.26
Generalized R^2			0.999			1.000			0.999
Equation Adjusted R^2									
Production Function			0.957			0.963			0.949
Capital Cost Share			0.779			0.796			0.781
Labor Cost Share			0.751			0.765			0.696
Materials Cost Share			0.875			0.884			0.858

Table 6. Parameter estimates, metalworking machinery (SIC 354).

Year	1992			1997			2002		
Variable	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.
constant	7.152	0.014	0.00	7.382	0.016	0.00	7.560	0.017	0.00
ln K	0.085	0.001	0.00	0.124	0.001	0.00	0.135	0.001	0.00
ln L	0.562	0.003	0.00	0.520	0.002	0.00	0.505	0.003	0.00
ln E	0.016	0.000	0.00	0.014	0.000	0.00	0.013	0.000	0.00
ln M	0.308	0.002	0.00	0.300	0.001	0.00	0.294	0.002	0.00
$(\ln K)^2$	0.064	0.001	0.00	0.080	0.001	0.00	0.080	0.001	0.00
$(\ln L)^2$	0.183	0.002	0.00	0.175	0.002	0.00	0.141	0.002	0.00
$(\ln E)^2$	0.013	0.000	0.00	0.013	0.000	0.00	0.011	0.000	0.00
$(\ln M)^2$	0.170	0.001	0.00	0.174	0.001	0.00	0.154	0.001	0.00
ln K · ln L	-0.038	0.001	0.00	-0.046	0.001	0.00	-0.047	0.001	0.00
ln K · ln E	-0.001	0.000	0.00	-0.001	0.000	0.00	-0.001	0.000	0.00
ln K · ln M	-0.029	0.000	0.00	-0.038	0.001	0.00	-0.040	0.001	0.00
ln L · ln E	-0.006	0.000	0.00	-0.006	0.000	0.00	-0.005	0.000	0.00
ln L · ln M	-0.140	0.001	0.00	-0.131	0.001	0.00	-0.119	0.001	0.00
ln E · ln M	-0.006	0.000	0.00	-0.006	0.000	0.00	-0.006	0.000	0.00
C	-0.088	0.041	0.03	-0.200	0.041	0.00	-0.190	0.052	0.00
AL	-0.512	0.973	0.60	-2.826	0.936	0.00	0.060	0.630	0.92
ln AI	0.024	0.017	0.15	0.030	0.018	0.09	-0.040	0.018	0.03
ln AS	-0.012	0.013	0.36	-0.046	0.016	0.00	0.025	0.017	0.14
ln AR	-0.029	0.010	0.00	0.005	0.011	0.65	-0.019	0.011	0.08
ln AP	0.076	0.017	0.00	0.083	0.015	0.00	0.106	0.017	0.00
C^2	0.287	0.287	0.32	0.821	0.277	0.00	-0.052	0.328	0.87
C · AL	-1.368	4.734	0.77	-2.749	3.265	0.40	0.801	2.585	0.76
C · ln AI	-0.095	0.080	0.23	0.023	0.085	0.79	-0.099	0.084	0.24
C · ln AS	0.051	0.050	0.30	0.041	0.060	0.49	0.132	0.073	0.07
C · ln AR	0.013	0.037	0.73	-0.040	0.037	0.27	-0.018	0.044	0.68
C · ln AP	0.035	0.076	0.65	0.029	0.057	0.62	-0.121	0.068	0.07
C · ln K	0.004	0.003	0.13	0.008	0.003	0.02	0.019	0.005	0.00
C · ln L	-0.025	0.011	0.03	-0.030	0.010	0.00	0.000	0.012	0.98
C · ln E	-0.001	0.001	0.10	0.001	0.001	0.26	0.001	0.001	0.42
C · ln M	0.023	0.007	0.00	0.028	0.006	0.00	0.031	0.008	0.00
AL · ln K	-0.050	0.068	0.46	-0.072	0.076	0.35	0.048	0.061	0.44
AL · ln L	0.407	0.291	0.16	0.167	0.217	0.44	0.594	0.170	0.00
AL · ln E	0.055	0.023	0.02	-0.066	0.019	0.00	-0.063	0.013	0.00
AL · ln M	-0.020	0.181	0.91	0.040	0.137	0.77	0.128	0.108	0.24

Year	1992			1997			2002		
Variable	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.
ln AI · ln K	0.003	0.001	0.01	0.001	0.002	0.75	-0.001	0.002	0.70
ln AI · ln L	0.008	0.005	0.10	0.004	0.005	0.41	-0.015	0.006	0.01
ln AI · ln E	-0.001	0.000	0.01	0.000	0.000	0.35	0.000	0.000	0.52
ln AI · ln M	0.010	0.003	0.00	-0.001	0.003	0.77	-0.004	0.004	0.24
ln AS · ln K	-0.002	0.001	0.01	-0.002	0.001	0.12	0.003	0.002	0.08
ln AS · ln L	-0.006	0.003	0.08	0.002	0.004	0.57	0.023	0.005	0.00
ln AS · ln E	0.001	0.000	0.00	0.000	0.000	0.82	0.000	0.000	0.30
ln AS · ln M	-0.006	0.002	0.00	-0.001	0.003	0.85	0.010	0.003	0.00
ln AR · ln K	0.000	0.001	0.64	0.001	0.001	0.53	-0.002	0.001	0.05
ln AR · ln L	0.005	0.003	0.08	-0.010	0.003	0.00	-0.010	0.003	0.00
ln AR · ln E	0.001	0.000	0.00	0.001	0.000	0.00	0.001	0.000	0.00
ln AR · ln M	0.002	0.002	0.38	0.002	0.002	0.27	-0.004	0.002	0.05
ln AP · ln K	-0.001	0.001	0.35	0.003	0.001	0.05	0.001	0.002	0.60
ln AP · ln L	0.002	0.005	0.74	0.004	0.004	0.38	0.012	0.005	0.01
ln AP · ln E	0.001	0.000	0.05	0.001	0.000	0.00	0.001	0.000	0.16
ln AP · ln M	-0.004	0.003	0.25	0.005	0.003	0.06	0.000	0.003	0.96
D	0.178	0.017	0.00	0.210	0.016	0.00	0.217	0.018	0.00
S	-0.173	0.011	0.00	-0.125	0.011	0.00	-0.158	0.014	0.00
R1	-0.025	0.022	0.26	0.077	0.023	0.00	-0.014	0.028	0.61
R2	0.014	0.016	0.36	0.067	0.019	0.00	0.034	0.020	0.09
R3	-0.085	0.025	0.00	0.007	0.023	0.76	-0.097	0.031	0.00
ln POP	0.036	0.009	0.00	0.016	0.008	0.06	0.021	0.012	0.08
UE	0.589	0.347	0.09	-0.113	0.630	0.86	2.159	0.753	0.00
ln INC	-0.024	0.075	0.75	-0.105	0.072	0.15	-0.187	0.083	0.02
DV	-3.146	1.390	0.02	-4.041	1.342	0.00	-4.031	1.293	0.00
CH	-0.018	0.037	0.63	-0.014	0.036	0.69	0.222	0.042	0.00
DVH	0.557	1.024	0.59	-0.920	0.756	0.22	-0.497	1.065	0.64
Generalized R^2			0.999			0.999			0.999
Equation Adjusted R^2									
Production Function			0.942			0.952			0.935
Capital Cost Share			0.761			0.758			0.754
Labor Cost Share			0.745			0.739			0.737
Materials Cost Share			0.851			0.878			0.858

Table 7. Parameter estimates, measuring devices (SIC 382).

Year	1992			1997			2002		
Variable	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.
constant	8.279	0.027	0.00	8.491	0.027	0.00	8.773	0.048	0.00
ln K	0.094	0.001	0.00	0.122	0.002	0.00	0.128	0.002	0.00
ln L	0.431	0.005	0.00	0.398	0.005	0.00	0.396	0.006	0.00
ln E	0.011	0.000	0.00	0.009	0.000	0.00	0.008	0.000	0.00
ln M	0.374	0.005	0.00	0.377	0.004	0.00	0.367	0.005	0.00
$(\ln K)^2$	0.072	0.001	0.00	0.073	0.001	0.00	0.065	0.002	0.00
$(\ln L)^2$	0.135	0.004	0.00	0.121	0.003	0.00	0.121	0.004	0.00
$(\ln E)^2$	0.008	0.000	0.00	0.009	0.000	0.00	0.006	0.000	0.00
$(\ln M)^2$	0.146	0.003	0.00	0.158	0.003	0.00	0.145	0.003	0.00
ln K · ln L	-0.036	0.001	0.00	-0.026	0.001	0.00	-0.026	0.002	0.00
ln K · ln E	0.000	0.000	0.43	-0.002	0.000	0.00	-0.001	0.000	0.00
ln K · ln M	-0.040	0.001	0.00	-0.048	0.001	0.00	-0.043	0.001	0.00
ln L · ln E	-0.003	0.000	0.00	-0.002	0.000	0.00	-0.002	0.000	0.00
ln L · ln M	-0.108	0.003	0.00	-0.107	0.002	0.00	-0.105	0.003	0.00
ln E · ln M	-0.005	0.000	0.00	-0.005	0.000	0.00	-0.004	0.000	0.00
C	-0.353	0.183	0.05	-0.250	0.144	0.08	0.118	0.179	0.51
AL	1.326	0.843	0.12	0.365	0.615	0.55	-0.268	0.889	0.76
ln AI	-0.022	0.026	0.40	0.028	0.019	0.13	-0.004	0.022	0.87
ln AS	0.003	0.023	0.90	-0.017	0.018	0.34	-0.017	0.024	0.48
ln AR	0.024	0.012	0.04	0.017	0.010	0.09	0.011	0.013	0.40
ln AP	0.091	0.044	0.04	0.082	0.039	0.04	0.061	0.042	0.15
C^2	1.219	0.951	0.20	2.706	1.217	0.03	-3.046	1.720	0.08
C · AL	7.862	4.016	0.05	-3.220	3.825	0.40	-6.706	5.826	0.25
C · ln AI	-0.109	0.140	0.44	0.115	0.118	0.33	-0.372	0.182	0.04
C · ln AS	0.071	0.107	0.51	-0.173	0.109	0.11	0.157	0.132	0.24
C · ln AR	-0.013	0.053	0.81	0.058	0.062	0.36	-0.139	0.076	0.07
C · ln AP	0.025	0.275	0.93	0.118	0.262	0.65	0.626	0.305	0.04
C · ln K	0.007	0.007	0.27	-0.003	0.009	0.74	-0.005	0.012	0.65
C · ln L	0.064	0.022	0.00	0.035	0.021	0.10	0.024	0.027	0.39
C · ln E	-0.004	0.001	0.01	-0.005	0.002	0.00	-0.002	0.001	0.08
C · ln M	0.036	0.018	0.04	0.024	0.019	0.22	-0.004	0.024	0.88
AL · ln K	-0.505	0.067	0.00	-0.097	0.059	0.10	0.169	0.087	0.05
AL · ln L	-1.369	0.212	0.00	0.010	0.149	0.95	0.334	0.199	0.09
AL · ln E	-0.002	0.014	0.91	-0.011	0.013	0.38	-0.025	0.009	0.01
AL · ln M	-1.371	0.180	0.00	-0.417	0.134	0.00	-0.044	0.176	0.80

Year	1992			1997			2002		
Variable	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.	Coeff.	Std. Err.	p-Val.
ln AI · ln K	0.010	0.002	0.00	0.003	0.002	0.10	0.003	0.002	0.20
ln AI · ln L	0.028	0.006	0.00	0.004	0.005	0.33	0.004	0.006	0.49
ln AI · ln E	0.001	0.000	0.00	0.000	0.000	0.70	0.001	0.000	0.00
ln AI · ln M	0.030	0.005	0.00	0.006	0.004	0.17	0.010	0.005	0.05
ln AS · ln K	-0.005	0.002	0.00	-0.003	0.002	0.11	-0.004	0.002	0.08
ln AS · ln L	-0.016	0.005	0.00	-0.001	0.004	0.89	-0.001	0.006	0.82
ln AS · ln E	-0.001	0.000	0.07	0.000	0.000	0.82	-0.001	0.000	0.00
ln AS · ln M	-0.019	0.005	0.00	-0.005	0.004	0.23	-0.014	0.005	0.01
ln AR · ln K	-0.001	0.001	0.54	-0.001	0.001	0.17	0.001	0.001	0.48
ln AR · ln L	0.013	0.003	0.00	0.009	0.003	0.00	0.005	0.003	0.12
ln AR · ln E	0.000	0.000	0.36	0.000	0.000	0.40	0.000	0.000	0.00
ln AR · ln M	0.003	0.003	0.23	-0.002	0.002	0.37	0.001	0.003	0.71
ln AP · ln K	0.000	0.003	0.96	-0.001	0.003	0.79	0.004	0.004	0.29
ln AP · ln L	0.027	0.011	0.01	0.017	0.008	0.05	0.028	0.009	0.00
ln AP · ln E	-0.001	0.001	0.22	0.001	0.001	0.07	0.000	0.000	0.27
ln AP · ln M	-0.003	0.009	0.72	0.002	0.007	0.76	-0.002	0.008	0.78
D	0.231	0.035	0.00	0.251	0.032	0.00	0.275	0.036	0.00
S	-0.272	0.029	0.00	-0.254	0.026	0.00	-0.222	0.031	0.00
R1	0.019	0.037	0.61	-0.008	0.032	0.81	-0.089	0.051	0.08
R2	-0.007	0.039	0.87	-0.024	0.039	0.54	-0.117	0.043	0.01
R3	0.015	0.033	0.65	0.077	0.031	0.01	-0.080	0.053	0.13
ln POP	-0.013	0.032	0.68	0.049	0.021	0.02	0.076	0.027	0.00
UE	-0.807	1.320	0.54	-2.820	1.348	0.04	1.527	2.072	0.46
ln INC	-0.307	0.136	0.02	-0.091	0.129	0.48	-0.092	0.158	0.56
DV	-22.144	7.819	0.00	-9.545	5.659	0.09	-5.854	8.807	0.51
CH	-0.064	0.110	0.56	0.111	0.086	0.20	0.028	0.103	0.78
DVH	1.110	6.508	0.86	3.980	3.760	0.29	-4.138	6.506	0.52
Generalized R^2			0.998			0.998			0.998
Equation Adjusted R^2									
Production Function			0.941			0.946			0.937
Capital Cost Share			0.746			0.763			0.676
Labor Cost Share			0.655			0.646			0.621
Materials Cost Share			0.803			0.837			0.790

Table 8. Alternative Agglomeration Economy Spatial Decay Profiles for Plastics and Rubber (SIC 30).

	Labor Pooling (AL)	Manufactured Inputs (AI)	Producer Services (AS)	Research (AR)
Year: 1992				
α = 0.1, D_{max} = 50, 50	0.518 (0.297)	0.011 (0.278)	0.005 (0.654)	0.000 (0.795)
α = 0.1, D_{max} = 75, 200 (default)	0.900 (0.129)	0.005 (0.670)	-0.005 (0.657)	0.002 (0.862)
α = 0.1, D_{max} = 100, 300	0.596 (0.345)	-0.007 (0.585)	-0.011 (0.356)	0.021 (0.045)
α = 0.5, D_{max} = 75, 200	-1.440 (0.463)	0.238 (0.000)	-0.192 (0.000)	0.041 (0.138)
α = 1.0, D_{max} = 75, 200	0.540 (0.180)	0.008 (0.362)	0.006 (0.401)	0.004 (0.334)
α = 1.0 except 0.1 for AS, D_{max} = 75, 200	0.289 (0.301)	0.014 (0.016)	-0.012 (0.121)	0.005 (0.227)
Year: 1997				
α = 0.1, D_{max} = 50, 50	0.150 (0.587)	0.000 (0.971)	0.001 (0.936)	0.001 (0.467)
α = 0.1, D_{max} = 75, 200 (default)	0.040 (0.902)	0.000 (0.976)	0.000 (0.967)	0.007 (0.315)
α = 0.1, D_{max} = 100, 300	0.050 (0.889)	-0.003 (0.804)	-0.004 (0.743)	0.011 (0.214)
α = 0.5, D_{max} = 75, 200	0.048 (0.870)	-0.006 (0.527)	0.009 (0.377)	0.012 (0.049)
α = 1.0, D_{max} = 75, 200	-0.035 (0.869)	0.001 (0.869)	0.005 (0.435)	0.005 (0.179)
α = 1.0 except 0.1 for AS, D_{max} = 75, 200	-0.163 (0.295)	0.007 (0.173)	-0.008 (0.281)	0.004 (0.218)
Year: 2002				
α = 0.1, D_{max} = 50, 50	0.681 (0.017)	-0.007 (0.524)	0.029 (0.009)	-0.002 (0.383)
α = 0.1, D_{max} = 75, 200 (default)	0.686 (0.046)	-0.011 (0.410)	0.016 (0.222)	0.005 (0.502)
α = 0.1, D_{max} = 100, 300	0.696 (0.067)	-0.010 (0.486)	0.014 (0.337)	0.015 (0.163)
α = 0.5, D_{max} = 75, 200	0.772 (0.014)	-0.016 (0.201)	0.030 (0.012)	0.010 (0.180)
α = 1.0, D_{max} = 75, 200	0.479 (0.037)	-0.011 (0.246)	0.022 (0.009)	0.007 (0.109)
α = 1.0 except 0.1 for AS, D_{max} = 75, 200	0.064 (0.700)	0.010 (0.075)	-0.008 (0.284)	0.009 (0.041)

Notes: the first figure for D_{max} is the cutoff for labor pooling, manufactured inputs, and producer services; the second is for research. All distances in miles.

Table 9. Alternative Agglomeration Economy Spatial Decay Profiles for Metalworking Machinery (SIC 354).

	Labor Pooling (AL)	Manufactured Inputs (AI)	Producer Services (AS)	Research (AR)
Year: 1992				
α = 0.1, D_{max} = 50, 50	0.738 (0.355)	0.002 (0.896)	0.003 (0.837)	0.002 (0.232)
α = 0.1, D_{max} = 75, 200 (default)	-0.512 (0.599)	0.024 (0.152)	-0.012 (0.364)	-0.029 (0.003)
α = 0.1, D_{max} = 100, 300	-0.781 (0.480)	0.019 (0.318)	-0.009 (0.523)	-0.026 (0.046)
α = 0.5, D_{max} = 75, 200	-0.224 (0.756)	0.014 (0.342)	0.001 (0.930)	-0.016 (0.084)
α = 1.0, D_{max} = 75, 200	-0.199 (0.680)	0.010 (0.304)	0.000 (0.995)	-0.001 (0.911)
α = 1.0 except 0.1 for AS, D_{max} = 75, 200	-0.188 (0.667)	0.010 (0.142)	-0.011 (0.232)	0.002 (0.767)
Year: 1997				
α = 0.1, D_{max} = 50, 50	-1.602 (0.029)	0.013 (0.365)	-0.020 (0.145)	0.000 (0.987)
α = 0.1, D_{max} = 75, 200 (default)	-2.826 (0.003)	0.030 (0.086)	-0.046 (0.004)	0.005 (0.646)
α = 0.1, D_{max} = 100, 300	-2.098 (0.057)	0.020 (0.356)	-0.033 (0.091)	0.003 (0.811)
α = 0.5, D_{max} = 75, 200	-2.338 (0.003)	0.011 (0.490)	-0.026 (0.059)	0.013 (0.184)
α = 1.0, D_{max} = 75, 200	-0.804 (0.132)	-0.001 (0.943)	-0.005 (0.622)	0.007 (0.184)
α = 1.0 except 0.1 for AS, D_{max} = 75, 200	-0.762 (0.030)	-0.002 (0.733)	-0.020 (0.016)	0.008 (0.167)
Year: 2002				
α = 0.1, D_{max} = 50, 50	-0.196 (0.718)	-0.034 (0.030)	0.034 (0.032)	-0.005 (0.012)
α = 0.1, D_{max} = 75, 200 (default)	0.060 (0.925)	-0.040 (0.026)	0.025 (0.138)	-0.019 (0.079)
α = 0.1, D_{max} = 100, 300	-0.227 (0.754)	-0.063 (0.003)	0.021 (0.255)	0.017 (0.244)
α = 0.5, D_{max} = 75, 200	0.231 (0.686)	-0.034 (0.046)	0.030 (0.049)	-0.024 (0.026)
α = 1.0, D_{max} = 75, 200	-0.165 (0.707)	-0.016 (0.194)	0.018 (0.116)	-0.014 (0.037)
α = 1.0 except 0.1 for AS, D_{max} = 75, 200	-0.778 (0.019)	-0.003 (0.679)	0.003 (0.736)	-0.013 (0.043)

Notes: the first figure for D_{max} is the cutoff for labor pooling, manufactured inputs, and producer services; the second is for research. All distances in miles.

Table 10. Alternative Agglomeration Economy Spatial Decay Profiles for Measuring and Controlling Devices (SIC 382).

	Labor Pooling (AL)	Manufactured Inputs (AI)	Producer Services (AS)	Research (AR)
Year: 1992				
α = 0.1, D_{max} = 50, 50	-0.311 (0.864)	0.008 (0.037)	-0.045 (0.139)	0.046 (0.003)
α = 0.1, D_{max} = 75, 200	-0.934 (0.777)	-0.013 (0.057)	-0.060 (0.265)	0.040 (0.286)
α = 0.1, D_{max} = 100, 300	1.032 (0.843)	-0.029 (0.081)	-0.066 (0.307)	0.061 (0.132)
α = 0.5, D_{max} = 75, 200	1.398 (0.344)	-0.015 (0.036)	-0.033 (0.292)	0.050 (0.032)
α = 1.0, D_{max} = 75, 200 (default)	1.326 (0.116)	-0.022 (0.026)	0.003 (0.896)	0.024 (0.044)
α = 1.0 except 0.1 for AS, D_{max} = 75, 200	1.293 (0.107)	-0.023 (0.020)	-0.026 (0.435)	0.023 (0.052)
Year: 1997				
α = 0.1, D_{max} = 50, 50	-2.186 (0.065)	0.053 (0.027)	-0.035 (0.179)	0.028 (0.040)
α = 0.1, D_{max} = 75, 200	-1.648 (0.414)	0.069 (0.043)	-0.047 (0.198)	0.005 (0.840)
α = 0.1, D_{max} = 100, 300	0.571 (0.813)	0.058 (0.132)	-0.055 (0.136)	0.015 (0.549)
α = 0.5, D_{max} = 75, 200	0.226 (0.821)	0.044 (0.076)	-0.023 (0.346)	0.029 (0.130)
α = 1.0, D_{max} = 75, 200 (default)	0.365 (0.553)	0.028 (0.131)	-0.017 (0.345)	0.017 (0.092)
α = 1.0 except 0.1 for AS, D_{max} = 75, 200	0.571 (0.337)	0.021 (0.199)	-0.032 (0.308)	0.015 (0.158)
Year: 2002				
α = 0.1, D_{max} = 50, 50	-1.344 (0.348)	-0.010 (0.746)	-0.026 (0.517)	0.017 (0.363)
α = 0.1, D_{max} = 75, 200	-0.462 (0.842)	-0.009 (0.809)	-0.024 (0.655)	0.030 (0.228)
α = 0.1, D_{max} = 100, 300	0.567 (0.859)	-0.003 (0.944)	0.034 (0.629)	0.001 (0.976)
α = 0.5, D_{max} = 75, 200	-0.166 (0.904)	-0.007 (0.815)	-0.026 (0.450)	0.030 (0.243)
α = 1.0, D_{max} = 75, 200 (default)	-0.268 (0.763)	-0.004 (0.872)	-0.017 (0.484)	0.011 (0.398)
α = 1.0 except 0.1 for AS, D_{max} = 75, 200	0.209 (0.801)	-0.011 (0.515)	-0.014 (0.673)	0.005 (0.684)

Notes: the first figure for D_{max} is the cutoff for labor pooling, manufactured inputs, and producer services; the second is for research. All distances in miles.

Agglomeration Economies – Default Specifications

In Tables 5 through 7, regional labor pools have relatively small effects on production that vary across years and industries. For measuring and controlling devices, a two percent rise (roughly a standard deviation) in the labor pooling measure is associated with a 2.7% increase in output in 1992, less than one percent in 1997, and becomes negative in 2002, though only the 1992 figure is close to statistical significance at conventional levels. In the metalworking machinery industry, labor pooling is only significant in 1997 and shows a negative productivity impact. Plastics and rubber plants benefit from labor pooling potential in 1992 and 2002 at significant or close to significant levels, but in 1997 the effect is negligible. Labor pooling is the only one of the five agglomeration economy variables measured on a relative rather than an absolute scale, so its influence may be diluted by the other size-sensitive agglomeration variables as well as the population density control.

Supply pooling—both manufactured inputs and producer services—demonstrates few discernible and unambiguous impacts on production. The estimated coefficients are rarely large enough to be important and in most of the industries and years the coefficients of the two variables are of opposite sign. Colinearity between the two variables may be obscuring individual effects on production.

The results are stronger for the two knowledge spillover variables. Academic research expenditures generate a positive though still small productivity benefit for plants in the measuring devices industry: a doubling of the index of proximate academic research raises output between one and two percent. The effect is significant in 1992 and 1997 but not in 2002. The relatively small size of the impact is not entirely unexpected, as basic research influences production largely in the very long term and the research expenditures variable concerns only one of the mechanisms by which universities affect local economic performance. This positive influence is not evident in the other study industries. In the metalworking machinery production models, local academic research actually is a significantly negative factor for two of the three study years. Higher technology industries, such as measuring devices, stand to gain more from localized spillovers of basic research and knowledge.

Regional patenting activity substantially boosts production across all three industries. The impacts are greater than with the other agglomeration variables. In 1997 and 2002, a doubling of the regional patent rate in relevant technology fields is associated with two percent

higher output in plastics and rubber establishments.[10] The effects are larger for the other study industries. In 1992, the productivity gain to metalworking machinery establishments from doubling regional patenting is about eight percent; in 2002 the figure is over ten percent. In the measuring and controlling devices industry the corresponding impacts have trended downward, from nine percent in 1992 to six percent in 2002. Even with the smallest of these estimates, regional private sector innovation is a strong enough influence to suggest a possible route for local or regional policy measures to influence productivity.

The absence of strong, consistent results for several of the agglomeration measures may be related to the distribution of plant locations. Most of the plants in all three study industries are located in urban and metropolitan areas. Plants located in regions with few industry establishments were excluded from the analysis. Both factors constrain variation by removing the lower tail of the distribution of the agglomeration measures and may make it more difficult statistically to discern their influence on productivity.

Considering interactions involving the agglomeration variables, several of the myriad interaction terms between the agglomeration economies and standard inputs are significant, particularly those involving the labor pooling and knowledge spillover variables. These factor-altering characteristics of the agglomeration variables are more consistent over time than across industries, but still show variation in sign and significance across model years. Two of the more consistent effects are that labor pooling restrains energy usage and local patenting tends to stimulate the use of additional labor inputs. As for interactions of agglomeration with regional industrial concentration, for most of the industry-year pairs there is no pattern observed among a mix of positive and negative values. In other words, agglomeration advantages are not highly influenced by the degree of concentration with the regional industry.

Agglomeration Economies – Alternative Distance Decays

The estimated effects of potential agglomeration externalities may vary with the spatial scale, as contrasting degrees of proximity reveal differences in the patterns of interfirm and intraregional interactions. Conversely, the extent of the variation witnessed also indicates the robustness of the results described above that were obtained under the default agglomeration

[10] The estimated coefficient in 1992 is approximately one eighth as large, perhaps indicating that the plastics and rubber industry only began to benefit from private sector innovation in the last fifteen years or so. The discrepancy also could be due to changes in assignment propensities for patent technology classifications.

variable specifications.

For each industry, three decay factors of $\alpha = 0.1$, $\alpha = 0.5$, and $\alpha = 1.0$ are imposed. Three distance cutoffs are applied to the broadest decay factor of $\alpha = 0.1$.[11] These are $D_{max} = 50$ miles, $D_{max} = 75$ miles, and $D_{max} = 100$ miles for labor pooling (*AL*), manufactured inputs (*AI*), and producer services (*AP*), and $D_{max} = 50$ miles, $D_{max} = 200$ miles, and $D_{max} = 300$ miles for university research (*AR*). The sixth decay profile keeps the default distance cutoffs of $D_{max} = 75$ miles for the labor and supply pooling measures and $D_{max} = 200$ miles for research, and combines the gradual decay factor of $\alpha = 0.1$ for producer services with the steeper decay of $\alpha = 1.0$ for the remaining three spatially attenuating agglomeration variables. This final profile, the only one presented that incorporates dissimilar decay factors across agglomeration variables, is aimed at testing the specific observation made by Feser (2002) with regard to the farm and garden machinery (SIC 352) and measuring devices industries that proximity to producer services is important at a regional scale whereas proximity to manufactured inputs is much more tightly localized. Tables 8 through 10 report the estimated coefficients for the four intraregionally spatially variant agglomeration variables as the model is re-estimated under the six decay profiles. Appendix Tables B-1 through B-3 provide the descriptive statistics for the permutations of the agglomeration measures, equivalently to Table 3.

Labor pooling remains only rarely significant across all of the nine industry-year models and six spatial decay profiles. For those industries and years in which the default labor pooling variable is significant and positive, altering the spatial decay profiles generally does not improve the strength of the labor pooling coefficient or the magnitude of its impact. This supports previous findings that labor pooling is equally important (or insignificant) at both small and large spatial scales (Rosenthal and Strange 2001; Renski 2006). Within the measuring devices industry, there is a tendency for the estimated coefficient to become negative as the decay factor steepens ($\alpha = 0.5$ or $\alpha = 1.0$) or the distance cutoff is reduced ($D_{max} = 75$ miles or $D_{max} = 50$ miles), suggesting that labor pooling advantages accrue at the wider regional scale. This contradicts indications demonstrated in Feser (2002) with regard to the same industry that labor pooling effects are narrow in spatial extent.

The two supply pooling measures continue to be obstructed by colinearity; the additional

[11] The distance cutoff is unimportant with the steeper decays because the distance decay factor discounts severely the potential agglomeration economy influences at intermediate to large distances.

spatial permutations add little to the results obtained under the default spatial decay profiles. Even the sixth decay profile that combines gradual distance decay in producer services with steeper distance decay of the other three spatial agglomeration variables remains occluded, generating small coefficients of opposite sign for the two supply pooling variables, and thus failing to either support or negate Feser's (2002) observation of different spatial scales for producer services and manufactured inputs agglomeration externalities. Nor does the mixed decay profile yield substantially different coefficient magnitudes or significance levels for the labor pooling or research agglomeration variables.

Under the default spatial profiles, proximity to academic research expenditures yields positive benefits only to the measuring devices industry and not to the two traditional manufacturing industries. The production gain for measuring devices establishments is one to two percent from doubling the research measure from the sample mean. Table 10 demonstrates that the effect increases in importance with a less precipitous distance decay. When α is reduced from 1.0 to 0.5, the magnitude of the impact approximately doubles. Further reduction to α = 0.1, however, diminishes the effect again. In the plastics and rubber industry, though the default coefficients are small, moderate spatial decay also maximizes the estimated benefits from research proximity. Across the nine industry-year pairs, greater distance cutoffs are associated with greater elasticities more often than not. These results imply that productivity benefits from proximity to relevant academic research expenditures are produced over sizable distances.

Finally, it is worth noting that the interaction terms with regional industrial concentration change only within a very restricted range, remaining small and mostly insignificant, with no particular patterns discernible across the varying agglomeration decay profiles. There also is little change in the estimated marginal impact of other variables, such as patenting.[12]

SUMMARY AND CONCLUSIONS

This study gauges the impact and spatial patterns of multiple types of agglomeration externalities through estimating fully-specified establishment-level production function systems. Alternate distance decay profiles are applied to the construction of spatially varying agglomeration measures. The strongest empirical findings are garnered for the two knowledge spillover agglomeration variables indicating knowledge spillovers. Proximate academic research

[12] Since these estimates are not central, they are not presented here, but are available from the author.

positively influences production in the measuring devices industry, and regional patenting yields substantial benefits across all of the study industries. Potential labor and supply pooling externalities, on the other hand, produce small effects on plant output that vary across years and industries.

The exercise of varying the spatial parameters defining the agglomeration measures suggests that the advantages of labor pooling and knowledge spillovers arise at relatively wide, regional scales. This finding supports the contention that agglomeration economy mechanisms requiring less frequency of face-to-face interactions successfully span greater distances. The results also are consistent with the idea that distance is more of a hindrance to productivity enhancements from agglomeration externalities in innovation-intensive industries. As embodied in the default decay profiles, the measuring devices industry tends to display greater sensitivity to agglomeration defined with narrower distance cutoffs and steeper distance decays, whereas production in the other two industries is more heavily impacted by agglomeration at broader spatial scales.

Variation in the spatial patterns across industries is substantial, as much as or more than across the five agglomeration measures, suggesting that industry characteristics are at least as important in determining the spatial dimension of agglomeration as the externality mechanism. Nevertheless, the evidence demonstrates that overall, while there are some interesting regularities, the influence of potential agglomeration externalities on production does not vary greatly according to the particular spatial decay contour imposed. Therefore, the results obtained under the default specifications are to a large degree robust with regard to the spatial decay profile.

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APPENDIX A: PRODUCTION FUNCTION VARIABLES AND CONSTRUCTION

Table A-1. Production Function Variables and Sources.

Category	Variable		Description	Source
dependent variable	Q	output	value of output	LRD
standard inputs	K	capital	gross book assets plus (capitalized) rentals	LRD
	L	labor	production-worker-equivalent hours	LRD
	E	energy	value of electricity and fuels	LRD
	M	materials	value of purchased materials and services	LRD
concentration	C	concentration	percent of shipments in dominator firms	LRD
agglomeration economies	AL	labor pooling	percent of local employment in top industry occupations	Census, BLS
	AI	inputs pooling	local employment in input supply industries	LBD, BEA
	AS	producer services	local employment in producer service industries	LBD, BEA
	AR	research	university research expenditures in industry-relevant fields	NSF
	AP	patents	per capita industry-relevant patent rate	USPTO
establishment size	D	dominator	dummy: establishment belongs to dominant firm	LRD
	S	dominated	dummy: shipments less than 10 percent of smallest dominator	LRD
controls	R1	region	dummy: South Census Region	Census
	R2	region	dummy: Midwest Census Region	Census
	R3	region	dummy: West Census Region	Census
	POP	population	population density (persons per square mile)	Census
	UE	unemployment	unemployment rate	BLS
	INC	income	median household income in region (nominal dollars)	Census
	DV	diversity	Herfindahl index of regional industrial diversity (concentration)	LBD
	CH	historic concentratio	dominance in earlier year	LRD
	DVH	historic diversity	diversity (concentration) in earlier year	LBD

LRD = Longitudinal Research Database, LBD = Longitudinal Business Database, BLS = Bureau of Labor Statistics (Staffing Patterns Matrix), BEA = Bureau of Economic Analysis (*Benchmark Input-Output Accounts*: Make and Use tables), NSF = National Science Foundation (CASPAR), USPTO = U.S. Patent and Trademark Office (Utility Patent Reports), Census = U.S. Bureau of the Census (decennial censes, population estimates, *Small Area Income and Poverty Estimates*).

Units: Monetary values are thousands of nominal dollars. Time measures are thousands of hours.

Inputs and Output: Variables are calculated at the establishment level. Output (Q) is the total value of shipments adjusted for inventories and work in progress:

$$Q = TVS + (WIE - WIB) + (FIE - FIB)\,.$$

TVS is the total value of shipments; *WIE* and *WIB* are work in progress at the end and beginning of the year; *FIE* and *FIB* are end-of-year and beginning-of-year finished product inventories.

Capital is constructed as a gross stock measure—the sum of end-of-year capital assets and capitalized building and machinery rental expenditures:

$$K = TAE + \frac{BR}{BPR} + \frac{MR}{MPR}.$$

TAE is total end-of-year building and machinery assets; *BR* is building rental expenditures; *MR* is machinery rental expenditures; *BPR* and *MPR* are (unpublished) annual national 3-digit-SIC capital prices obtained from the Bureau of Labor Statistics averaged across asset categories.

Labor (*L*) is production-worker-equivalent hours, derived as the ratio of total wages to production worker average hourly wages:

$$L = \frac{WP + WNP}{(WP / PH)}.$$

WP and *WNP* are production and non-production payrolls; *PH* is production worker hours.

Energy (*E*) is the sum of purchased electricity and fuel quantities:

$$E = CF\left(\frac{1{,}000}{EPR}\right) + PE\left(\frac{3{,}412.705}{1{,}000}\right).$$

PE is millions of British Thermal Units of purchased electricity; *CF* is purchased fuels cost; *EPR* is the average state-level industry-specific energy price from the U.S. Energy Information Administration *State Energy Data System*.

Materials (*M*) is the total cost of materials, parts, contract work, resales, purchased services, and repairs, adjusted for changes in materials inventories:

$$M = CP + CR + CW + CPC + RB + RM + (MIB - MIE).$$

CP is materials and parts cost; *CR* is expenditures for resales; *CW* is contract work costs; *CPC* is purchased communications services; *RB* and *RM* are building and machinery repairs; *MIB – MIE* is the difference between beginning- and end-of-year materials inventories.

Capital costs are total capital assets adjusted by multiplying by (unpublished) Bureau of Labor Statistics capital asset prices and LRD-reported building and machinery rental costs. Labor costs are total wages and salaries plus supplemental labor expenditures. Energy costs are purchased electricity and fuels costs. Materials costs are identical to the quantity measure.

Control Variables: Regional unemployment rates, household incomes, and population densities are constructed for LMAs by combining county-level estimates. Unemployment rates are from the Bureau of Labor Statistics *Local Area Unemployment Statistics*. Median household income levels are from Census *Small Area Income and Poverty Estimates*. Population density is

calculated from Census population estimates. Establishment-level data from the LBD are used to construct regional industrial diversity and historic diversity measures. Because the LBD starts in 1977, the historic diversity measure for the 1992 sample is from 1977.

APPENDIX B: ALTERNATIVE AGGLOMERATION VARIABLES

Table B-1. Descriptive Information for Alternative Agglomeration Economy Variables, Plastics and Rubber (SIC 30).

Year / Sample observations	1992 (n = 6,747)			1997 (n = 8,000)			2002 (n = 6,546)		
	mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Labor Pooling (AL)									
α = 0.1, D_{max} = 50	0.0784	0.0147	35.27	0.0979	0.0277	41.56	0.1180	0.0311	44.23
α = 0.1, D_{max} = 75 (default)	0.0781	0.0129	39.32	0.0974	0.0249	42.76	0.1171	0.0279	44.70
α = 0.1, D_{max} = 100	0.0773	0.0113	44.89	0.0962	0.0224	44.98	0.1156	0.0251	46.96
α = 0.5, D_{max} = 75	0.0778	0.0134	40.91	0.0968	0.0255	41.16	0.1165	0.0286	43.95
α = 1.0, D_{max} = 75	0.0794	0.0161	42.06	0.0989	0.0295	40.28	0.1193	0.0333	42.21
Manufactured Inputs (AI)									
α = 0.1, D_{max} = 50	1,904	1,565	34.15	1,157	996	38.18	1,036	909	37.37
α = 0.1, D_{max} = 75 (default)	2,913	2,071	42.00	1,807	1,356	40.68	1,635	1,212	40.90
α = 0.1, D_{max} = 100	4,141	2,683	49.36	2,585	1,759	42.76	2,356	1,554	44.01
α = 0.5, D_{max} = 75	1,031	897	34.50	633	534	37.66	565	503	39.47
α = 1.0, D_{max} = 75	561	751	34.79	342	437	33.46	301	415	30.87
Producer Services (AS)									
α = 0.1, D_{max} = 50	17,821	22,137	29.98	8,567	10,138	32.24	9,256	11,184	32.86
α = 0.1, D_{max} = 75 (default)	25,567	28,550	27.95	12,517	13,345	30.88	13,878	15,073	30.58
α = 0.1, D_{max} = 100	34,738	35,059	29.67	17,312	16,754	27.26	19,315	18,776	26.93
α = 0.5, D_{max} = 75	9,005	8,499	35.27	4,511	4,141	36.19	4,903	4,747	34.56
α = 1.0, D_{max} = 75	4,701	4,979	37.22	2,461	2,735	34.63	2,627	3,203	32.83
Research (AR)									
α = 0.1, D_{max} = 50	71,605	83,042	34.27	80,817	90,614	39.63	91,193	104,659	39.38
α = 0.1, D_{max} = 200 (default)	330,729	242,436	38.94	406,037	274,997	41.69	501,543	322,954	41.87
α = 0.1, D_{max} = 300	531,526	320,542	50.44	657,110	378,881	51.38	823,065	449,876	51.36
α = 0.5, D_{max} = 200	68,816	53,056	37.28	83,401	59,327	41.20	99,783	68,342	43.26
α = 1.0, D_{max} = 200	22,600	34,996	28.04	27,315	41,560	26.05	30,717	48,011	24.43

Note: All distances in miles.

Table B-2. Descriptive Information for Alternative Agglomeration Economy Variables, Metalworking Machinery (SIC 354).

Year / Sample observations	1992 (n = 5,189)			1997 (n = 5,490)			2002 (n = 4,161)		
	mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Labor Pooling (AL)									
α = 0.1, D_{max} = 50	0.1187	0.0118	46.73	0.1473	0.0157	55.43	0.1246	0.0229	55.30
α = 0.1, D_{max} = 75 (default)	0.1170	0.0109	47.95	0.1457	0.0145	55.01	0.1221	0.0204	56.28
α = 0.1, D_{max} = 100	0.1156	0.0103	44.96	0.1446	0.0140	51.91	0.1202	0.0190	56.79
α = 0.5, D_{max} = 75	0.1187	0.0126	46.41	0.1465	0.0152	54.68	0.1228	0.0211	53.40
α = 1.0, D_{max} = 75	0.1212	0.0158	41.53	0.1491	0.0179	49.95	0.1263	0.0246	51.77
Manufactured Inputs (AI)									
α = 0.1, D_{max} = 50	2,233	1,513	38.81	2,026	1,330	42.28	1,845	1,261	41.41
α = 0.1, D_{max} = 75 (default)	3,297	1,883	48.20	3,025	1,650	47.74	2,797	1,609	45.61
α = 0.1, D_{max} = 100	4,650	2,399	54.83	4,311	2,143	55.23	4,030	2,112	52.30
α = 0.5, D_{max} = 75	1,238	805	40.10	1,119	714	40.86	1,014	658	41.65
α = 1.0, D_{max} = 75	722	637	35.36	644	577	38.09	571	517	39.17
Producer Services (AS)									
α = 0.1, D_{max} = 50	14,840	17,005	36.89	6,591	7,279	38.00	6,954	8,031	38.02
α = 0.1, D_{max} = 75 (default)	22,113	22,927	31.18	9,866	9,857	30.46	10,660	11,130	30.09
α = 0.1, D_{max} = 100	31,771	29,590	26.31	14,119	12,604	24.75	15,587	14,594	24.35
α = 0.5, D_{max} = 75	7,992	6,878	34.69	3,573	3,078	35.37	3,801	3,556	34.17
α = 1.0, D_{max} = 75	4,386	4,199	36.37	1,973	2,044	34.77	2,068	2,358	33.12
Research (AR)									
α = 0.1, D_{max} = 50	90,523	119,538	38.27	126,233	157,162	35.81	142,452	178,397	35.38
α = 0.1, D_{max} = 200 (default)	497,467	377,447	38.95	725,256	475,313	39.69	924,617	555,602	44.20
α = 0.1, D_{max} = 300	951,010	530,637	34.92	1,355,860	697,026	42.39	1,736,869	814,152	49.15
α = 0.5, D_{max} = 200	97,856	82,525	34.26	140,113	101,366	35.92	173,752	118,158	41.43
α = 1.0, D_{max} = 200	28,966	58,476	22.26	39,650	74,452	21.64	47,170	87,304	20.33

Note: All distances in miles.

Table B-3. Descriptive Information for Alternative Agglomeration Economy Variables, Measuring Devices (SIC 382).

Year / Sample observations	1992 (n = 1,384)			1997 (n = 1,540)			2002 (n = 1,201)		
	mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Labor Pooling (AL)									
α = 0.1, D_{max} = 50	0.1307	0.0112	47.90	0.1887	0.0161	47.27	0.1464	0.0169	50.46
α = 0.1, D_{max} = 75	0.1275	0.0077	47.69	0.1845	0.0119	49.09	0.1438	0.0139	61.95
α = 0.1, D_{max} = 100	0.1258	0.0066	50.58	0.1822	0.0104	52.14	0.1422	0.0126	61.62
α = 0.5, D_{max} = 75	0.1322	0.0133	38.01	0.1904	0.0190	43.12	0.1476	0.0198	43.38
α = 1.0, D_{max} = 75 (default)	0.1369	0.0201	39.45	0.1958	0.0265	42.53	0.1514	0.0259	40.88
Manufactured Inputs (AI)									
α = 0.1, D_{max} = 50	4,029	2,863	40.82	4,683	4,771	30.13	4,396	3,922	34.39
α = 0.1, D_{max} = 75	5,271	3,275	47.76	5,775	4,800	40.00	5,468	3,991	43.96
α = 0.1, D_{max} = 100	6,658	3,724	50.36	6,971	4,806	44.81	6,647	4,143	47.96
α = 0.5, D_{max} = 75	2,445	2,172	31.14	3,063	4,100	22.92	2,746	3,201	27.56
α = 1.0, D_{max} = 75 (default)	1,728	2,167	25.22	2,374	4,113	18.31	2,051	3,194	22.90
Producer Services (AS)									
α = 0.1, D_{max} = 50	22,171	18,588	35.91	13,041	10,158	35.32	15,391	11,760	42.71
α = 0.1, D_{max} = 75	29,855	24,932	33.38	17,418	13,974	31.95	20,658	16,416	37.72
α = 0.1, D_{max} = 100	38,327	31,018	23.84	22,230	17,705	21.49	26,050	20,572	30.89
α = 0.5, D_{max} = 75	11,816	6,746	44.22	7,084	4,055	48.64	8,428	5,014	46.54
α = 1.0, D_{max} = 75 (default)	7,089	4,425	50.51	4,401	3,039	47.79	5,268	3,809	46.54
Research (AR)									
α = 0.1, D_{max} = 50	351,894	324,155	36.49	404,162	359,165	39.42	455,715	369,934	42.80
α = 0.1, D_{max} = 200	976,528	693,341	42.56	1,168,589	827,246	39.61	1,349,064	878,821	44.13
α = 0.1, D_{max} = 300	1,508,751	971,866	46.17	1,849,187	1,211,985	45.78	2,166,647	1,325,504	49.71
α = 0.5, D_{max} = 200	287,981	237,962	42.41	338,027	277,223	40.58	379,065	270,459	40.13
α = 1.0, D_{max} = 200 (default)	160,186	229,831	22.90	185,002	267,781	29.48	201,325	261,265	27.81

Note: All distances in miles.