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ABSTRACT

This paper extends the research in Carlino, Chatterjee, and Hunt (2007) to examine the effects of local economic characteristics on the rate of innovation (as measured by patents) in more than a dozen industries. The availability of human capital is perhaps the most important factor explaining the invention rate for most industries. We find some evidence that higher job market density is associated with more patenting in industries such as pharmaceuticals and computers. We find evidence of increasing returns with respect to city size (total jobs) for many industries and more modest effects for increases in the size of an industry in a city. This suggests that inter-industry spillovers are often at least as important as intra-industry spillovers in explaining local rates of innovation. A more competitive local market structure, characterized by smaller establishments, contributes significantly to patenting in nearly all industries. More often than not, specialization among manufacturing industries is not particularly helpful, but we find the opposite for specialization among service industries. Industries benefit from different local sources of R&D (academia, government labs, and private labs) and to varying degrees.

I. INTRODUCTION

This paper examines the role metropolitan areas play in the production of ideas. The academic literature has identified a variety of geographically localized forces that influence innovation. Theories by Berliant, Reed, and Wang (2006), hereafter BRW (2006), and Helsley and Strange (2002) stress the superiority of matches that can be formed among agents in cities. For example, BRW (2006) argue that in dense urban areas, workers are more selective in their matches and are therefore more productive.[1]

The examination of dynamic spillovers associated with matching externalities is relatively new and is in part motivated by the emergence of endogenous growth theory in the late 1980s. But there is also a much older literature that stresses the importance of static thick-market externalities in generating innovation, such as urban agglomeration economies. There has been an ongoing debate as to whether innovation is enhanced in local areas with industrial structures that are highly specialized industrially or if more diverse places are better at fostering innovation. Economists have also debated the importance of the competitiveness of a local area (or lack thereof) on the rate of innovation among local firms.

Existing studies have tended to focus on one type of externality. For example, the study by Ó hUallacháin 1999 looks at the empirical relationship between metropolitan area population size and patenting in metropolitan areas. A recent paper by Carlino, Chatterjee, and Hunt (2007), hereafter CCH (2007), considers how a number of localized forces influenced the rate of patenting in metropolitan areas in the 1990s. Our paper is similar to CCH (2007), in that we consider how urban density, urban scale, an area's

[1] For a generalization of the model in BRW (2006), see Hunt (2007).

industrial structure, the availability of research inputs in an area (i.e., private R&D labs), etc, effect the rate of innovation as measured by patents issued to inventors in a metropolitan area. But our paper differs from CCH (2007) in that we focus on the effects of these factors on the invention rate at the level of 17 industry groups. It's likely that the importance of localized knowledge spillovers and the benefits of geographic clustering for innovation differ significantly across industries. One advantage of using industry data is that it gives a much larger testing ground for understanding the local forces that govern innovation.

II. LITERATURE REVIEW

There is substantial evidence for a link between the geographic concentration of population/economic activity and innovation. For example, in the 1990s, 92 percent of all patents were granted to residents of metropolitan areas, although only about three-quarters of the U.S. population resides in metropolitan places. Economists have offered two reasons why innovative activity is more efficient in cities than outside them: knowledge spillovers and thick market effects.

Knowledge Spillovers Although many factors contribute to growth, the recent endogenous growth literature has argued that *uncompensated* knowledge spillovers may play an important role. If the diffusion of tacit knowledge is to any degree retarded by distance, the concentration of workers in cities can capitalize on these spillovers by creating an environment in which ideas flow quickly among workers and firms.

To date, economists have provided limited, but tantalizing, evidence on the existence and importance of these spillovers. Jaffe et al. (1993) find that nearby inventors have a much higher propensity to cite each others' patents, suggesting that knowledge spillovers are indeed localized. But their study does not explain how city characteristics, such as size and local density, influence the production of these spillovers.

CCH (2007) find that, all else equal, patent intensity (patents per capita) is 20 percent higher in a metropolitan area with an employment density (jobs per square mile) twice that of another metropolitan area. Ciccone and Hall (1996) find that county employment densities help to explain differences in productivity levels across states. In their study of inventor network effects, Strumsky, Lobo, and Fleming (2005), report a positive relationship between the number of patents and population density in 331 MSAs. Andersson, Burgess, and Lane (2004) show that the correlation between workers' skills (education) and employers' productivity (revenue per worker) at the establishment level is larger in counties with higher population densities. They argue that this is evidence of superior matching between workers and firms in more dense labor markets.

There also is evidence that localized knowledge spillovers tend to attenuate rapidly with distance from the source of these externalities. For example, Rosenthal and Strange (2001) find that knowledge spillovers tend to be highly localized. They consider the importance of input sharing, matching, and knowledge spillovers for manufacturing firms at the state, county, and zip code levels of geography. They find the effects of knowledge spillovers on agglomeration of manufacturing firms tend to be quite localized, influencing agglomeration only at the zip code level. Jaffe (1986) finds evidence that localized knowledge spillovers dissipate rapidly for patent citations. Arzaghi and Henderson (2005) find knowledge flows among advertising agencies in Manhattan tend to be extremely localized.

Thick Market Effects A number of researchers stress the importance of a metropolitan area's size for innovation. Large metropolitan areas have numerous inventors and plenty of R&D activities that are focused on innovations. Several authors find that patent activity increases with metropolitan area size as measured by population or total employment (Feldman and Audretsch 1999, Ó hUallacháin 1999, and Bettencourt, Lobo, and Strumsky 2004). But these studies do not control for inputs into the innovation process, such as R&D, and therefore cannot identify the external effects.

A recent paper by Helsley and Strange (2002) offers micro-foundations for a link between innovation and input sharing. The idea is that a dense network of input suppliers, as found in metropolitan areas, facilitates innovation by making it less costly to bring new ideas to fruition. As Helsley and Strange (2002) note, "concentrations encourage innovation by assisting in the realization of ideas rather than in (or perhaps in addition to) the generation of ideas."

Industries Level Studies Some studies have tended to look at innovation within a particular industry, such as the semi-conductor or pharmaceuticals industries. While these studies are quite informative, most often these studies lack a spatial component. Studies that have a spatial component most often look at aggregate innovation in cities and metropolitan areas and in general ignore the sectoral dimension. There are a few exceptions. A paper by Anselin, Varga, and Acs (1997) looks for evidence of local university spillovers for four two-digit industries located in MSAs. They find evidence of university research spillovers in the electronics and instruments industries but not in the drugs and chemical industry or in the machinery industry.

Economists also have debated the effects of local market structures (e.g., degree of local market competition and degree of diversity in an area's industrial structure) on the rate of innovation and growth. Once again, the vast majority of this research has been for aggregate variables in cities and metropolitan areas. One exception is the paper by Henderson, Kuncoro, and Turner (1995) who examined employment growth rates in five traditional capital goods industries located in 224 cities. For mature industries in these sectors, they found that employment growth was positively correlated with a high past concentration in the same industry, while industrial diversity was found to be most important for growth of less established industries.

In this paper, we explicitly examine the effects of *employment density* (jobs per square mile), city size (total employment), industry size (share of MSA employment in a given industry) and other characteristics (e.g., specialization and local competition) on the rate of innovation across metropolitan areas in the U.S. We use the average level of patents during 1990 to 1999 in a metropolitan area as a measure of innovative activity in these areas. Specifically, we look at total patents and patents in each of 17 industries in 280 metropolitan areas in the 1990s. Unlike past studies that have focused analysis on a single or a few determinants of local innovation (e.g., university research), we allow for a much richer set of influences (knowledge spillovers, thick market effects, the effects of private R&D and university R&D, etc.).

By considering patents at the industry level we can observe if there are differences in the benefits that local labor markets offer to the various industries. In addition to examining the role that industrial concentration plays in the innovation process, we allow for two types of thick market effects: those associated with industrial clusters (localization economies) and those associated with the overall scale of a city (urbanization economies). Other studies have focused on only one aspect, such as the size of a local area or industrial structure or competitiveness. In this paper we look at the various ways in which a local area contributes to innovative activity.

III. OUR DATA AND REGRESSION STRATEGY

Since data on innovations are not generally available at the local level, we use the level of patents in a metropolitan area as our measure of innovation. This measure has its shortcomings, since some innovations are not patented and patents differ enormously in their economic impact.[2] Nonetheless, patents remain a useful measure of the generation of ideas.

We regress patents in each of 17 industries in a metropolitan area on measures of local employment density (labor market matching), MSA employment size (urbanization economies), MSA industry size (localization economies) and a variety of control variables. More specifically, the dependent variables in our regressions is the total number of patents issued in an MSA over the period 1990-99 to each of the 17 major industries comprising this study.[3] We use total patents by industry averaged over the period 1990-1999 to minimize any effects from year-to-year fluctuations in patent activity, which could be an issue in smaller metropolitan areas or if the presence of an industry in an area is low. Table 1 gives a detailed description of our broad industrial categories. To mitigate any bias induced by endogeneity or reverse causation, the

[2] For a general discussion of patents as indicators, see Griliches (1990, 1994).

[3] Our patent data are from the USPTO's US Patent Inventor File and the PATSIC99 file. We thank Jim Hirabayashi of the USPTO for his assistance in obtaining and explaining these data.

independent variables to be described in detail below are at 1989-90, or roughly beginning-of-the-period values.[4]

Following CCH (2007), the sample consists of 280 metropolitan areas as defined in 1983. For brevity, we refer to these as MAs. Included in this sample are 264 metropolitan statistical areas (MSAs) and primary metropolitan statistical areas (PMSAs). To include as many patents as possible in our data set, we grouped 25 component PMSAs into their corresponding nine consolidated metropolitan statistical areas (CMSAs). It was also necessary to group 21 separate MSAs into seven metropolitan areas.[5] This aggregation permits us to include an additional 9,000 patents (6.5 percent of the total) in our regressions.

The Patent Data. Patents are assigned to metropolitan areas according to the *residential* address of the first inventor named on the patent. We allocate patents to a county or metropolitan area when we can identify a unique match to either a county or metropolitan area. Patents that cannot be uniquely matched are excluded from our data set. We were able to locate over 581,000 patents granted over the 1990-99 period to inventors living in the U.S. to either a unique county or MA, a match rate of 96 percent. Just over 534,000 (92 percent) of these patents were associated with an urban county.

Industry Patent Counts. We depart from CCH (2007) in that we allocate our patents to 17 industries. We do this using the USPTO OTAF concordance for the 1999 vintage of the patent data. This is a mapping from *patent classifications*, as assigned by

[4] Details of the construction of our variables may be found in an appendix available from the authors.

[5] For details on these non-standard MAs, see the data appendix of CCH (2007). In that paper, we verified the regressions results were not sensitive to the exclusion of these MAs.

the examiner to industries that typically make or use these technologies.[6] One can think (very loosely) of patent classifications as a position in technology space (Jaffe 1986). These industries, and the share of our patents in them, are reported in Table 1.

We recognize this mapping is not a perfect one and, as a result, there is likely to be some measurement error in the assignment of patents to industries. To control for this, and also the possibility of persistence of local advantages in particular technologies or industries, we include lagged values of the *share* of jobs and patents in these industries in our regressions.[7] The lagged patent shares are based on patent activity in an MA during the 1980s and the lagged employment shares are based on data contained in the 1989 edition of *County Business Patterns*.

Land Area. By definition, employment density is the number of jobs per square mile of land area. Employment density varies enormously within metropolitan areas. It is typically highest in the central business district (CBD) of an MA's central city and generally falls off as we move away from the CBD. However, the majority of land area in most MSAs counties is in fact rural in nature. In the 1990 census only 12 percent of the 580,000 square miles of land in MSAs was categorized as urban in nature. There is also considerable variation in the degree to which the counties surrounding a central city are built out. The urban share of MSA land area in 1990 varied from less than 1 percent in Yuma, AZ, to 65 percent in Stamford, CT.

We use a measure of land area that reflects the interaction of workers in labor

[6] To be precise, we collapse 57 USPTO OTAF codes into 17 sets of two- and three-digit SIC codes, which we describe as industries. The remaining patents are grouped into an additional category, "other," which constitutes the omitted share in all our regressions.

[7] An alternative interpretation of the coefficients on these variables is that they are picking up spillovers across industries. At present, however, our specification cannot distinguish between these two possibilities.

markets that are sufficiently dense to call urban—the *urbanized area* (UA) of cities.[8] These are defined as continuously built-up areas with a population of 50,000 or more, comprising at least one *place* and the adjacent densely settled surrounding area with a population density of at least 1,000 per square mile (U.S. Census Bureau, 1994).[9]

Employment and Density. For our purposes, the ideal measure of jobs and employment density would count only those jobs located in the urbanized area of cities. Unfortunately, such data are generally unavailable. For example, our preferred measure of employment is derived from the BLS survey of payrolls. We also use these data in our measures of MA size.[10] The primary advantage of these data is that jobs are reported based on the *place of work* rather than the *place of residence*. The disadvantage is that the data are reported at the county or MSA level, but not for urbanized areas.

To the extent that some metropolitan employment occurs outside of urbanized areas, our MA employment density measure will overstate the actual density of jobs in the built-up portion of MAs. But the most likely effect of such measurement error in our regressions would be a negative bias in the coefficient on employment density.[11] That is because we include in our density measure jobs (in "rural" parts of the MA) less likely to be associated with innovation activities.

To investigate the potential effects of agglomeration economies on inventive

[8] Mills and Hamilton (1994, p. 6) argue that urbanized areas correspond most closely to the economist's notion of urban areas.

[9] While UAs often cross county lines, we collected data on urbanized area land in each county and then aggregated this number to the MA level.

[10] Our data on total employment, and job shares outside manufacturing, were extracted from the 1999 vintage of the BEA's Regional Economic Indicator System (REIS).

[11] In CCH (2007), we ran regressions for total patents per capita using alternative measures of employment density. We found that the findings were unaffected by the using a resident based measure of employment (e.g., from the census of population) as opposed to establishment based measures. In addition, we reported regressions where we instrument for our density measure to better control for possible endogeneity bias or measurement error.

output, we include three variables in all regressions that are reported. Total establishment-based employment in an MA and its square is used to test for the importance of net urbanization economies on patenting. The share of MA employment in each industry (in 1989) is also included.[12] The coefficient on the own industry employment share can be interpreted as a measure of localization economies for that economy. We expect a positive sign on both the net urbanization economies and localization economies variables.

Industrial Diversification and Local Market Structure. To explore the possible effects of local industrial diversification or specialization on inventive output, we construct two Herfindahl-Hirshman Indexes of industry employment shares. We calculate the sum of the square of MA manufacturing employment shares in 1989 accounted for by each two-digit SIC manufacturing industry and another using data for each one-digit SIC non-manufacturing industry.[13] Higher values of either index for an MA imply that its economy is more highly specialized.

To investigate the potential effects of local labor market structure on inventive output, we construct a variable similar to one suggested in Glaeser et al. (1992)—the number of establishments per worker in the metropolitan area. According to this definition, the higher this ratio, the more competitive is the local labor market.[14] This variable may capture more than a static sense of industrial structure. If cities, or industries

[12] We measure employment at the industry level using *County Business Patterns*, since this data allows us to construct shares that are consistent with our industry definitions. As noted above, we include the employment shares in the other industries in all our regressions.

[13] The index for manufacturing is derived from the *County Business Patterns* data and the index for non-manufacturing is based on data from BEA (REIS). We use the latter source for non-manufacturing since it includes government employees.

[14] The number of establishments is derived from the 1989 vintage of *County Business Patterns*.

within a city, are experiencing considerable entry or start-up activity, one would expect average establishment size to be smaller.

Local Research Inputs. Given that our regression relies on a cross section, it is important to take into account factors that influence the overall productivity in a city. We include many control variables for this purpose. We also control for the concentration of firms located in *high technology industries*. We do this by calculating the share of patents obtained in an MA for the years 1980-89 owned by firms in research-intensive industries as defined by the Commerce Department's Office of Technology Policy (2001).[15] And, as mentioned above, we also include the shares of patents obtained in each MA during 1980-89 for each of our 17 industries.

It is especially important to control for local inputs into the R&D process. For example, Andersson, Quigley, and Wilhelmsson (2005) find evidence that the expansion of the number of university-based researchers in a local labor market is positively associated with an increase in the number of patents granted in that area.[16] To account for the relative abundance of local human capital, our regressions include the share of the population (over 25 years of age) with a college degree or more education in 1990. We also control for the influence of having many nearby universities, a possible college town effect, by including the ratio of college enrollment to population in the years 1987-89.

We include three other measures of research inputs in terms of their *intensities*.[17] First, we include in our regressions the sum of spending on R&D in science and

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[15] This variable is constructed by matching patent numbers to assignees (firms) in the NBER Patent Citations Data File and obtaining a corresponding four-digit SIC code from Compustat. See CCH (2007) for details.

[16] See Anselin, Varga, and Acs (1997) for a review of the studies examining localized spillovers from university R&D.

[17] Not surprisingly, the *levels* of these inputs are highly correlated with city size.

engineering at local colleges and universities divided by full-time enrollment at colleges and universities in the MA over the years 1987-89. We hope to capture the intensive margin—the R&D resources available to potential researchers. Similarly, our regressions include the sum of federal funding at government research laboratories in the MA divided by the number of federal civilian employees in the MA (averaged over the period 1987-89). Finally, we include in our regressions the number of private R&D facilities in 1989 divided by the number of private non-farm establishments.[18]

Other Control Variables. Does a correlation between patent activity and our spillover variables (employment density, city size, or industry size) reflect an actual difference in inventive activity or, instead, differences in the way firms protect their inventions? For example, firms might rely more on patenting in dense areas or in areas when other firms in its industry are concentrated if it is more difficult to maintain trade secrets there than in less dense areas. In that case, greater difficulty in maintaining secrecy, rather than spillovers, might explain our results.

To test the significance of this alternative explanation, we create an index of the importance of trade secrecy that varies across metropolitan areas. We do this by weighting industry-specific measures of the effectiveness of trade secrecy reported in Cohen, Nelson, and Walsh (2000) by the industry shares reflected in the mix of private R&D facilities in every MA in our data set.[19] A higher value of this index for an MA implies that trade secrets are relatively more effective for the mix of industries reflected in its R&D facilities.

[18] Over 1,800 private labs associated with the top 500 R&D performing corporations were geographically located using information contained in the 1989 edition of the *Bowker Directory of American Research and Technology*.

[19] See CCH (2007) for details on the construction of this variable.

We include a number of other control variables. We include the percent change in employment over the years 1980-89 as a control for the effects of unobserved differences in local economic opportunities on inventive activity. We also include seven dummy variables based on the BEA economic region in which the MA is located (the Rocky Mountain region is omitted).

Table 2 shows the summary statistics for the variables used in the analysis. To begin with, we show the summary statistics for total patents and the summary statistics for patents for each of the 17 industries used in this study. For example, the number of total patents awarded to inventors during the 1990s—our measure of innovative activity—vary considerably across MAs. The number of patents runs from a high of almost 43,000 in the New York MA to 7 in Victoria, Texas MA, compared with an average of just over 1,900 for the typical MA in our sample. The number of patents by industry also displays considerably variation across cities. The mean number of patents varies from a high of 284 in communications equipment (including semiconductors in our taxonomy) to about 13 in the food industry. Even through the food industry tends to do little patenting, the number of patents in the industry runs from a high of 655 in the New York metropolitan area to zero patents in 75 metropolitan areas.

The urbanized land area of MAs varies considerably across cities: for Grand Forks it is less than 15 square miles; for New York-Northeastern New Jersey, it exceeds 3,000 square miles. Establishment-based employment in our MAs varies from 37,000 (Casper, WY) to 9.7 million (New York-Northeastern New Jersey). The mean of MA employment density is 1,727 jobs per square mile, while the mean of UA employment density is 987 jobs per square mile.

Our Specification. Our main regression equation is simply:

$$y_{ij} = C + a_1 D_i + a_2 D_i^2 + a_3 E_i + a_4 E_i^2 + a_5 COMP_i + a_6 hhi3_i + a_7 hhi\_nm_i + a_8 HITECH_i + \sum_{k=9}^{25} a_k PATSHR_{ik} + \sum_{g=26}^{43} a_g INDSHR_i$$

$$+ a_{44} PCTCOL_i + a_{45} CE_i + a_{46} U_i + a_{47} FEDLAB_i + a_{48} R\&D_i + a_{49} TS_i + a_{50} EMPGT_i + a_{51} non\_mfg\_sh + \sum_{r=52}^{58} a_r REGION_{ir} + \mu_i$$

where:

$y_{ij} =$ The level of total patents issued during the period 1990-99 in the j-th industry and i-th *MA*;

$D_i =$ Log of MA job density in 1989 in *i*;

$E_i =$ Log of 1989 level of employment in MA_i;

$COMP_i$ = Log of the number of establishments in MA_i divided by total employment in MA_i, in 1989;

$hhi3_i$ = Herfindahl-Hirshman Index of manufacturing industry employment shares in 1989 MA_i;

$hhhi\_nm_i$ = Herfindahl-Hirshman Index of non-manufacturing industry employment shares in 1989 MA_i;

$HITECH_i$ = Share of patents in MA_i during 1980-89 obtained by firms in R&D intensive industries;

$PATSHR_{ik}$ = Share of patents obtained in MA_i during 1980-89, classified in each of our17 industries;

$INDSHR_i$ = The share of CBP employment in our 17 industries in 1989 MA_i;

$PCTCOL_i$ = Percent of 1990 population over 25 with at least a college degree in MA_i;

$CE_i =$ Ratio of the college enrollment to population in *i*;

U_i = University R&D spending per student, averaged for 1987-89 in MA_i;

$FEDLAB_i =$ Federal lab R&D per federal civilan job, averaged for 1987-89 in MA_i;

$R\&D_i =$ Private lab R&D per establishment in 1989 in *i*;

TS_i = Trade Secrets Index = The log of a weighted average of ratings of the effectiveness of trade secret protection in *i*;

$EMPGT_i =$ The percent change in employment in MA_i during the period 1980-89;

$non\_mfg\_sh_i =$ The share of non-manufacturing employment in MA_i in1989;

$REGION_{ir}$ = dummy variables indicating in which of the eight BEA regions MA_i is located;

μ_i is the random error term.

Statistical Model Let y_{ij} denote the number of patents in *j*th industry in the *i*th MA. Since we will apply the same model to each industry in our sample, we drop the *j* subscripts here to simplify the notation. Because y_i is a discrete random count variable, it can be modeled as a Poisson distribution with parameter λ_i:

$$prob(Y_i = y_i \mid x_i) = \frac{\exp(-\lambda)\lambda^{y_i}}{y_i\,!}, \quad y_i = 0,\ 1,\ 2,\ 3, \cdots,$$

The Poisson regression model estimates the probability of the arrival rate λ_i of patents that occurs *n* times ($n = 1, 2, 3, \cdots$) as a function of a vector of independent variables. More precisely, λ_i is defined as an exponential function of x_i:

$$E(y_i \mid x_i) = \lambda_i = \exp(x_i \beta_i)$$

where β_i is the vector of parameters to be estimated.

One limitation of this model is that a Poisson random variable is distributed with a mean equal to the variance (equidispersion). If there is more variation than would be expected under a Poisson process (overdispersion) estimation of a Poisson model produces downward biased estimates of the variances. This is a common problem in empirical work and is often addressed by using the more general negative binomial specification. For each regression, we test for over-dispersion using a likelihood-ratio test developed by Cameron and Trivedi (1998). We reject the null hypothesis of zero over-dispersion in each of the 17 industries in this study. We therefore estimated a negative binominal model (for total patents and for patents in each of our 17 industries) using the maximum likelihood techniques in contained in STATA. All our results are presented using robust standard errors (White correction) to control for any heteroskedasticity.

IV. FINDINGS

Density and Scale Table 3 contains the estimates for negative binominal model for total patents, and for each of 17 industries. To conserve on space, Table 3 shows estimated coefficients and related statistics only for the main variables of analysis.[20] In all but two industries (fabricated metals, and other transportation equipment), the coefficient on our total employment density variable is positive. These coefficients are statistically significant in six industries: drugs, non-metal materials (oil and gas production, refining, rubber, stone, and other non-metallic materials), metal working machinery, computers, electric2 (household appliances, lighting and wiring, and other electric equipment), and communications equipment (which includes semiconductors) .

In CCH (2007), we argued that such a relationship was consistent with increasing efficiencies in the matching of workers and firms at higher densities found in the theoretical model of BRW (2006). There is also some evidence of congestion—in each of the six industries mentioned above, there is a negative and statistically significant coefficient on the square of job density.

Table 4 presents optimal density and optimal scale for the 17 industries, as well as the elasticities for a number of variables reported in Table 3. The optimal density level for total employment is about 2,016 jobs per square mile. That is about the 75th percentile of our data set, or roughly the densities associated with the Greensboro-Winston-Salem, North Carolina MA. This is very similar to the optimal density estimated using ordinary least squares in CCH (2007).[21]

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[20] Tables containing the full set of variables reported in Table 3 are available from the authors upon request.

[21] In that paper, the dependant was the log of patents per capita.

Considering only the significant coefficients, the optimal density varies from as high as 2,019 jobs per square mile for the communications equipment industry (which includes semiconductors) industry, to a low of 1,289 jobs per square mile for manufacturers of other machinery. The former value is roughly the density of the Greensboro-Winston-Salem (North Carolina) MA, while the latter corresponds to the density of the Fort Meyers (Florida) MA.

We now turn to our measures of scale, or what are often described as urbanization economies. Previous research has found evidence that innovation is positively related to metropolitan employment size (see, for example, Ó hUallacháin 1999, and Feldman and Audretsch 1999). But these papers do not allow for the possibility of congestion as suggested by the open city version of the model in BRW (2006). In CCH (2007), we found evidence of initially increasing returns to scale in patenting. But we also found that these scale economies were largely exhausted at roughly the mean of the distribution of city size in our data (roughly that of Austin, TX, or Raleigh-Durham, NC, in 1990). Here we examine whether these effects vary by industry.

Table 3 reports the estimated coefficients on both the log of MA employment and its square in our regressions. For every industry in this study, the level of establishment-based employment in an MA is positive and always statistically significant. That is hardly a surprising result given findings reported in the literature. But we again find some evidence of significant congestion effects for some industries: chemicals, drugs, metal working machinery, computers, other machinery, electrical equipment (power generation, distribution, and industrial apparatus), motor vehicles, and instruments.

Unless there are extremely large diseconomies of scale, we should expect the number of patents to increase with the size of MAs. As a first approximation, the level of patenting should increase proportionately with MA scale. We do not suggest this is evidence in favor of urbanization economies. A more appropriate measure would be some evidence of *increasing* returns to scale. In the second column of Table 4 we report estimates of the scale economies, evaluated at the *mean* of the distribution of city size in our data. As expected, all of the coefficients are above one in magnitude, and the ones in bold (12 industries) indicate that the estimated value is statistically different from one.[22] Interestingly, the largest estimates of economies of scale are associated with drugs (1.54), computers (1.42), and chemicals (1.26). These are also relatively patent intensive industries.

Our findings suggest that localization economies may also be an important determinant of innovative activity, for some (8 out of 17) of our industries. Recall that we estimate these effects using the coefficient on the industry's share of total employment in an MA. In one case, textiles, this coefficient is both negative and statistically significant, suggesting strong *within industry* diseconomies scale. For the remaining seven industries with a significant coefficient on our localization variable, the associated elasticities are relatively small, varying from 0.06 (in metal working machinery) to 0.14 (in non-metal materials).

On balance, then, it appears that urbanization economies in a number of industries appear to be at least as strong as any localization economies. This suggests an important source of spillovers may be arriving from outside the industry, a view suggested in the

[22] In addition, the test statistics for all patents and patents in non-metal materials are also marginally significant. The associated p values are 0.12 and 0.11, respectively.

research of Jacobs (1969). This finding is reinforced by the fact that coefficients on lagged values of patent shares for other industries in the MA are often statistically significant (not shown), which might also suggest the presence of significant inter-industry spillovers.

Local Competition. The bulk of the regressions suggest that the rate of innovation is enhanced in more competitive local environments characterized by many small firms, rather than in local economies dominated by a few large firms. The coefficient on the number of establishments per employee is about 1.3 in the total patent regression and is precisely measured. The coefficient can be interpreted as an elasticity since the variable is included in logs in our regression. The effect is economically significant, as this ratio more than doubles across the industries in our sample. The elasticity of patents with respect to local competition varies from 0.14 in the primary metals industry to 1.88 in both the computer and other transportation industries. For most industries this elasticity is quite large. In only one industry was this coefficient insignificant (drugs) and this telling, since the market structure of this industry is significantly determined by government regulation. Perhaps that is because the market structure on the industry may be determined by regulation (the FDA drug approval process) than by economic factors, at least relative to other industries.

These results are broadly consistent with the views of Chinitz (1961), Feldman and Audretsch (1999), Glaeser et al. (1992), and Jacobs (1969) that competitive local labor markets facilitate innovation.

Industrial Mix and Specialization. If knowledge spillovers occur largely within industries, specialized cities may be more efficient producers of inventions. On the other hand, if important spillovers are generated across industries, perhaps more industrially diverse cities may be more efficient innovators. To test for such effects, we include in our regressions, in logs, two Herfindahl-Hirshman Indexes of industry employment shares. The first measures the degree of specialization in two-digit SIC manufacturing industries, and the second measures the degree of specialization in one digit SIC non-manufacturing industries. We control for the relative importance of these two parts of the local economy by also including the non-manufacturing share of all jobs in 1989 as a control variable.

The estimated coefficient on our measure of manufacturing specialization is statistically significant in only six industries: food, textiles, primary metals, machinery, metal working machinery, and computers. The associated elasticities are about 0.3-0.4 in absolute value. The effects are positive in all but one industry—computers. Thus for most industries manufacturing specialization does not appear to be important; in less than a third of the industries it is associated with higher inventive productivity; but in computers it is associated with less inventive productivity. Keep in mind that our regression also includes the underlying manufacturing industry employment shares. A literal interpretation of this specification is that, conditional on that industry mix, there can be significant separate effects associated with the degree of specialization in manufacturing.

As for specialization outside of manufacturing, we find this is positively associated with patenting in 10 of 17 industries, and for patenting overall. The associated elasticities are relatively large, especially for drugs and computers where they exceed 2. We are unaware of any previous research that explores the significance of specialization in non-manufacturing on the rate of invention in manufacturing industries. We think these results warrant additional investigation.

Local Research Inputs. We also find that local research inputs are important to explaining the variation in patenting across MAs and across industries The coefficients on our controls for research-intensive industries is statistically significant in 10 of 17 industries and for patents overall (Table 5). But the associated elasticities are relatively small (0.1 to 0.2). These coefficients are likely reduced by the inclusion in our regressions of the shares of patents obtained in each industry over the previous decade.

Table 5 presents results for five other variables of interest. By far the most powerful effect is generated by human capital (the share of the adult population in an MA with at least a college degree). A 10 percent increase in this ratio is associated with a 5.9 percent increase in total patents. With the exception of the food, computers, motor vehicles and other transportation industries, this measure of human capital has a statistically significant effect on patenting in all other industries. Among the industries where this coefficient is statistically significant, the smallest elasticity among these industries (metal working machinery) is 0.4. These results are consistent with what we report in CCH (2007)—the presence of local human capital (the share of the adult population in an MA with at least a college degree) is by far the most important variable in explaining the rate of invention in cities.

We also included a variable to capture the relative size of higher education in a metropolitan area, measured by the ratio of college enrollment to the adult population. The coefficient on this variable is either generally insignificant or marginally significant in our regressions, suggesting that there is no separate college town effect on the local invention rate.

Our other controls for local research inputs include lagged values of academic R&D, R&D spending at nearby government labs, and private R&D, all included in intensity form (see section IV). Each of these variables has a statistically significant effect on the rate of patenting in most industries, and patenting overall. But, as we found in CCH (2007), the implied elasticities are relatively small (see Table 5). Still, these effects are economically significant since there is considerable variation in the intensity of both academic and private R&D intensity in our data (see Table 2).

There is also considerable variation in the magnitude of these effects across industries. For example, the chemical and drug industries especially benefit from increases in local human capital and in academic R&D performed by universities nearby (the elasticity associated with an increase in academic R&D intensity is 0.13 in Chemicals and 0.19 in drugs). On the other hand, the intensity of nearby private R&D labs does not appear to be important for patenting in drugs, while this elasticity is highest for the food (0.11) and computer (0.12) industries. The largest elasticity associated with R&D performed by government labs is found in the primary metals industry (0.03).

Trade Secret Protection. Recall that one interpretation of our coefficients on job market density is that firms are substituting patents for trade secrets in areas where the latter form of protection may be less effective. To test for such effects, we constructed a measure of the efficacy of trade secret protection across manufacturing industries and then weighted these measures using the local share of employment in these industries.

In our regressions we find a positive effect of our trade secrecy measure on overall patenting (Table 4). This suggests, if anything, that patents and trade secrets are complementary forms of protection. This is consistent with the correlation between industry level measures of the efficacy of patents and trade secrets reported in Cohen, Nelson, and Walsh (2000). At the industry level, this variable is only significant for six industries (chemicals, non-metal materials, primary metals, fabricated metal products, metal working machinery, and computers). For these industries, the elasticities are relatively large, in particular for computers and primary metals.

But it remains the case that city size and employment density remain important in explaining patent intensity even after controlling for an industry's reliance on trade secret protection. This suggests that we are measuring increases in the rate of invention and not simply substitution in the means of protecting inventions.

Employment Growth and Other Control Variables. The coefficient on employment growth in the previous decade is positive and statistically significant in the total patents main regression (Table 5). It is also has a positive and significant effect on patenting in 14 of our 17 industries. The associated elasticities vary from 0.12 in the machinery industry to 0.43 for primary metals. This suggests that, even after controlling for an MA's historical mix of industries and technologies, a considerable amount of unobserved heterogeneity remains to be explained.

The estimated coefficients on only one of the seven BEA region dummies (not shown) are statistically significant in the total patents regression. MAs located in the Southwest regions had lower patent intensities. But there are also differential regional effects in a number of our industries (not shown). Overall, it appears that our controls do a good job of accounting for the other factors that contribute to innovation in cities.

V. CONCLUSION

In this paper we explore the relationship between patenting at the industry level using a rich set of explanatory variables at the level of individual cities. This research builds on the results of CCH (2007) by decomposing our aggregate patenting data in that paper into measures for 17 groups of industries. This finer examination of the data requires a different econometric specification—in this case the negative binomial.

As in CCH (2007), we test for significant effects of city size and density on the research productivity of industries located in these cities. We also look for evidence of congestion. We find that job market density plays a role in explaining the patenting behavior of some of the most patent intensive industries, such as drugs, computers, and communications equipment (which includes semiconductors in our taxonomy) and the implied optimal density varies significantly across industries. Thus, at the industry level, there is qualified evidence in support of the labor market matching externality explored in BRW (2006).

We test for evidence of increasing returns to scale as well as the possibility of congestion that would imply that such returns must eventually diminish. We find evidence of both. The elasticity of output (in this case patenting) with respect to city size (total employment) exceeds one in 12 of our 17 industries, and by a significant margin for drugs (1.5), computers (1.4), and chemicals (1.3). This result is consistent with the argument that larger cities produce more spillovers that are enjoyed by the resident industries (urbanization economies). But we also find evidence of congestion effects in at least seven of our industries, including the ones mentioned above.

Another view of the dynamics of spillovers is that they tend to come from within industries, and we also find some evidence in support of this reasoning. In particular, the relative size of an industry affected the volume of patenting in about half of our industries, but the estimated elasticities seem relatively small (and in the case of textiles, it was negative), especially when compared to our estimates of the urbanization economies.

Consistent with our earlier research, we find the abundance of local human capital is a major determinant of the rate of patenting in most of our industries. The effects are especially pronounced for chemicals and drugs. We find that, at the margin, local investments in R&D by universities, government labs, and private firms produce modest but significant contributions to patenting in most industries. But the magnitude of these effects, and the most relevant sources of R&D, vary considerably by industry. For example, we find that academic R&D is clearly most important for patenting in chemicals and drugs, while the presence in private R&D labs is most important for patenting in food products and computers. The marginal effect of additional government R&D was largest for patenting in primary metals.

Once again we find that a more competitive local market structure, characterized by a smaller average establishment size, is associated with a higher rate of invention. Indeed this variable was statistically significant for every one of our industries except for drugs. Finally, we find that specialization among manufacturing industries positively influenced patenting in less than a third of industries, and actually reduced patenting in the computer industry. In contrast, we found that specialization among non-manufacturing industries was associated with more patenting in most of our manufacturing industries. The implied elasticity was especially large for drugs and computers. We believe this an entirely new finding and it warrants additional investigation.

REFERENCES

Andersson, Frederik, Simon Burgess, and Julia Lane, 2004, "Cities, Matching and Productivity Gains of Agglomeration," CEPR Discussion Paper No. 4598.

Andersson, Roland, J. Quigley, and M. Wilhelmsson, 2005, "Higher Education, Localization and Innovation: Evidence from a Natural Experiment," Unpublished manuscript.

Anselin, Luc, Attila Varga, and Zoltan Acs, 1997, "Local Geographic Spillovers Between University and High Technology Innovations," *Journal of Urban Economics*, Vol. 42, pp. 442-48.

Arzaghi, Mohammad, and J. Vernon. Henderson. "Networking off Madison Avenue," Unpublished manuscript, (2005).

Berliant, Marcus, Robert R. Reed, III and Ping Wang, 2006, "Knowledge Exchange, Matching, and Agglomeration," *Journal of Urban Economics*, Vol. 60, pp. 69-95.

Bettencourt, L., J. Lobo and D. Strumsky, 2004, "Invention in the City: Increasing Returns to Scale in Metropolitan Patenting," Los Alamos National Laboratory technical ReportLAUR-04-8798.

Cameron, A. Colin and Pravin K. Trivedi, 1998, *Regression Analysis of Count Data*, Econometric Society Monograph No.30, Cambridge University Press.

Carlino, Gerald, Satyajit Chatterjee, and Robert M. Hunt, 2007, "Urban Density and the Rate of Innovation," *Journal of Urban Economics*, Vol. 61, pp. 389-419.

Ciccone, Antonio, and Robert E. Hall, 1996, "Productivity and the Density of Economic Activity," *American Economic Review*, Vol. 86, pp. 54-70.

Chinitz, Benjamin, 1961, "Contrasts in Agglomeration: New York and Pittsburgh," *Papers and Proceedings of the American Economic Association,* Vol. 51, pp. 279-89.

Cohen, Wesley. M., Richard Nelson, and John P. Walsh, 2000, "Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (OR NOT)," NBER Working Paper No. 7552.

Directory of American Research and Technology, 23rd Edition, 1989, New York: R.R. Bowker.

Feldman, Maryann P., and David. B. Audretsch, 1999, "Innovation in Cities: Science-Based Diversity, Specialization and Localized Competition," *European Economic Review*, Vol. 43, pp. 409-29.

Glaeser, Edward L., Hedi D. Kallal, Jose A. Scheinkman, and Andrei Shleifer, 1992, "Growth in Cities," *Journal of Political Economy*, Vol. 100, pp. 1126-53.

Griliches, Zvi, 1990, "Patent Statistics as Economic Indicators: A Survey," *Journal of Economic Literature*, Vol. 28, pp. 1661-1707.

Griliches, Zvi, 1994, "Productivity, R&D, and the Data Constraint," *American Economic Review*, Vol. 84, pp. 1-23.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools," NBER Working Paper No. 8498.

Helsley, Robert W., and William Strange, 2002, "Innovation and Input Sharing," *Journal of Urban Economics*, Vol. 51, pp. 25-45.

Henderson, Vernon J., Ari Kuncoro, and Matt Turner, 1995, "Industrial Development in Cities," *Journal of Political Economy*, Vol. 103, pp. 1067-1090.

Hunt, Robert M. 2007. "Matching Externalities and Inventive Productivity," Federal Reserve Bank of Philadelphia Working Paper No. 07-7.

Jacobs, Jane, 1969, *The Economy of Cities*. New York: Vintage Books.

Jaffe, Adam. 1986. "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits and Market Value," *American Economic Review*, Vol. 76, pp. 984-1001.

Jaffe, Adam B., Manual Trajtenberg, and Rebecca Henderson, 1993, "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," *Quarterly Journal of Economics*, Vol. 108, pp. 577-98.

Mills, Edwin S., and Bruce W. Hamilton, 1994, *Urban Economics*, 5th ed. New York: Harper Collins College Publishers.

Ó hUallacháin , Breandán, 1999, "Patent Places: Size Matters," *Journal of Regional Science*, Vol. 39, pp. 613-36.

Rosenthal, Stuart S., and William C. Strange, 2001, "The Determinants of Agglomeration," *Journal of Urban Economics*, Vol. 50, pp. 191-229.

Strumsky, Deborah, Jose Lobo, and Lee Fleming, 2005, "Metropolitan Patenting, Inventor Agglomeration and Social Networks: A Tale of Two Effects," Los Alamos National Laboratory Technical Report LAUR-04-8798.

U.S. Census Bureau, 1994, Geographic Areas Reference Manual. http://www.census.gov/geo/www/garm.html

U.S. Department of Commerce, 2001, *The dynamics of technology-based economic development: state science and technology indicators, 2nd ed*., Office of Technology Policy, Washington, 2001.

U.S. Patent and Trademark Office, 2000, United States Patent Grants by State, County, and Metropolitan Area. Washington: U.S. Patent and Trademark Office, Office for Patent and Trademark Information. http://www.uspto.gov/web/offices/ac/ido/oeip/taf/county.pdf

Table 1: Industry Definitions

Industry	Description	Share of Total Patents
Food	Food & kindred products (SIC 20)	0.66%
Textiles	Textile mill products (SIC 22)	0.87%
Chemicals	Chemicals, except drugs & medicines (SIC 281-2, 284-9)	12.88%
Drugs	Drugs & medicines (SIC 283)	2.75%
Non-Metal Materials	Petroleum/natural gas extraction & refining; Rubber & miscellaneous plastics products; Stone, clay, glass & concrete products (SIC 13, 29, 30, 32)	7.58%
Primary Metals	Primary ferrous products; Primary & secondary non-ferrous metals (SIC 33, 3462-3)	0.64%
Fabricated Metal	Fabricated metal products (SIC 34 ex 3462-3 & 348)	6.51%
Machinery	Engines & turbines; Farm & garden machinery & equipment; Construction, mining & material handling machinery & equip. (SIC 351-3)	4.83%
Metal Working Machinery	Metal working machinery & equipment (SIC 354)	1.78%
Computers	Office computing & accounting machines (SIC 357)	8.62%
Other Machinery	Other machinery, except electrical (SIC 355-6, 358-9)	7.54%
Electric	Electrical transmission & distribution equipment Electrical industrial apparatus (SIC 361-2, 3825)	4.57%
Electric2	Household appliances; Electrical lighting & wiring equipment; Miscellaneous electrical machinery, equipment & supplies (SIC 363-4, 369)	2.60%
Communication	Radio & TV receiving equipment; Electrical components & accessories & communications equipment (SIC 365-7)	14.91%
Motor Vehicles	Motor vehicles & other motor vehicle equipment (SIC 371)	1.28%
Other Transp. Equipment	Guided missiles & space vehicles; Ship & boat building & repairing; Railroad equip; Motorcycles, bicycles & parts; Misc. transport equip.; Ordinance except missiles; Aircraft & parts (SIC 372-6, 348, 3795)	1.31%
Instruments	Professional & scientific instruments (SIC 38, except 3825)	12.60%

Table 2: Descriptive Statistics				
	Mean	SD	Min.	Max.
Total Patents, Avg. 1990-99	1906.5	4637.6	7	42702
Food Patents, Avg. 1990-99	12.6	52.4	0	655
Textile Patents, Avg. 1990-99	16.5	40.9	0	296
Chemicals Patents, Avg. 1990-99	245.5	772.5	0	9530
Drug Patents, Avg. 1990-99	52.4	178.1	0	1483
Non-Metal Materials Patents, Avg. 1990-99	144.5	345.5	1	3006
Primary Metal Patents, Avg. 1990-99	12.2	29.5	0	259
Fabricated Metal Patents, Avg. 1990-99	124.1	284.2	0	2333
Machinery Patents, Avg. 1990-99	92.0	196.8	0	1753
Metal Working Machinery Patents, Avg. 1990-99	34.0	80.7	0	830
Computer Patents, Avg. 1990-99	164.4	583.3	0	6963
Other Machinery Patents, Avg. 1990-99	143.8	303.0	0	2254
Electric Patents, Avg. 1990-99	87.1	222.3	0	1922
Electric2 Patents, Avg. 1990-99	49.5	135.2	0	987
Communication Patents, Avg. 1990-99	284.3	899.9	0	9174
Motor Vehicle Patents, Avg. 1990-99	24.5	111.5	0	1780
Other Transportation Patents, Avg. 1990-99	25.0	61.2	0	660
Instrument Patents, Avg. 1990-99	240.3	6680.8	0	5659
Urbanized Area Land Area, 1990	211.5	333.5	14.50	3015
MA Employment Density, 1990	1,727	689.3	408.1	5,021
MA Employment, 1989	392,480	862,483	37,375	9,665,015
Food Employment Share, 1989	0.0035	0.0065	0.00001	0.0560
Textile Employment Share, 1989	0.0036	0.0132	0	0.1311
Chemicals Employment Share, 1989	0.01097	0.0011	0	0.1677
Drug Employment Share, 1989	0.0016	0 .0047	0	0.0390
Non-Metal Materials Employment Share, 1989	0.0231	0.0214	0.0009	0.1426
Primary Metal Employment Share, 1989	0.0117	0.0230	0	0. .2547
Fabricated Metal Employment Share, 1989	0.0170	0.0159	0.0003	0.1165
Machinery Employment Share, 1989	0.0063	0.0163	0	0.1934
Metal Working Mach. Employment Share, 1989	0.0032	0.0060	0	0.0499
Computer Employment Share, 1989	0.0039	0.0130	0	0.1308
Other Machinery Employment Share, 1989	0.0115	0.0129	0.0001	0.1246
Electric Employment Share, 1989	0.0033	0.0064	0	0.0478
Electric2 Employment Share, 1989	0.0069	0.0208	0	0.2603
Communication Employment Share, 1989	0.0101	0.0206	0	0.1808
Motor Vehicle Employment Share, 1989	0.0103	0.0260	0	0.2522
Other Transportation Employment Share, 1989	0.0116	0.0356	0	0.4914
Instrument Employment Share, 1989	0.0095	0.0158	0	0.1215
Establishments per 100,000 Employees, 1989	4425	597.8	2667	6365
HHI of Mfg. Industry Employment Shares, 1989	436.3	535.9	3.3151	6015.6

Table 2: Descriptive Statistics, Continued				
	Mean	SD	Min.	Max.
HHI of Non-Mfg. Industry Emp. Shares, 1989	1376.0	271.2	543.6	3137.6
Non Manufacturing Employment Share, 1989	0.8508	0.0745	0.5394	0.9818
College Educated, 1990 (percent)	19.54	6.235	8.100	45.40
Enrolled in College, 1987-89 (percent)	6.661	5.423	0	34.06
University R&D Spending ($1,000) per Student, Avg. 1987-89	.5623	.9324	0	5.297
Federal Lab R&D Spending ($1,000) per Federal Civilian Employee, 1987-89	1.396	10.81	0	161.4
Private R&D Labs per 1,000 Establishments, 1989	.3037	.3863	0	2.710
Trade Secrets Index	50.96	5.382	34.04	70.69
MA Employment Growth, 1979-89 (percent)	20.47	15.54	-25.80	77.69
New England Region dummy	.0571	0.2325	0	1
Mideast Region dummy	0.1179	0.3230	0	1
Great Lakes Region dummy	0.1786	0.3837	0	1
Planes Region dummy	0.09286	0.2907	0	1
Southeast Region dummy	0.2821	0.4508	0	1
Southwest Region dummy	0.1107	0.3143	0	1
Rocky Mountain Region dummy	0.0357	0.1859	0	1
Far West Region dummy	0.1250	0.3313	0	1

See Section IV for details of variable construction and data sources

Table 3: Negative Binominal Regressions						
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Food	Textiles	Chemicals	Drugs	Non-Metal Materials
Job Density†	3.311 (1.62)*	2.857 (0.52)	6.520 (1.14)	4.085 (1.10)	16.337 (2.62)***	4.849 (1.99)**
Square of Job Density†	-0.218 (1.58)	-0.195 (0.53)	-0.437 (1.13)	-0.268 (1.07)	-1.097 (2.61)***	-0.320 (1.95)*
Jobs†	1.148 (10.06)***	1.277 (4.72)***	1.324 (5.01)***	1.553 (7.63)***	2.157 (5.77)***	1.216 (9.38)***
Square of Jobs†	-0.016 (1.09)	-0.010 (0.33)	-0.034 (1.09)	-0.050 (1.98)**	-0.107 (2.44)**	-0.024 (1.56)
Industry Share of Jobs	N/A	3.317 (0.76)	-13.843 (2.94)***	7.698 (2.30)**	10.977 (0.49)	6.061 (2.30)**
Establishments per 100,000 Employees†	1.272 (6.78)***	1.268 (2.38)**	1.429 (2.28)**	1.272 (3.46)***	0.195 (0.33)	1.402 (5.38)***
Manufacturing Specialization (HHI)†	0.062 (0.92)	0.347 (1.77)*	0.434 (2.78)***	0.034 (0.27)	-0.185 (0.67)	0.127 (1.62)
Non- Manufacturing Specialization (HHI)†	0.466 (1.95)*	-0.326 (0.56)	-0.776 (0.98)	0.337 (0.72)	2.038 (2.16)**	0.701 (2.21)**
Human Capital#	3.032 (4.43)***	1.018 (0.58)	5.133 (3.33)***	4.444 (3.78)***	4.545 (2.38)***	3.238 (4.07)***
Academic R&D#	0.127 (4.06)***	0.189 (2.45)**	0.138 (1.69)*	0.229 (3.55)***	0.334 (3.44)***	0.073 (2.10)**
Government Lab R&D#	0.007 (3.74)***	0.007 (1.27)	0.015 (2.35)**	0.008 (2.66)***	0.009 (1.81)*	0.005 (2.32)**
Private R&D#	0.255 (3.60)***	0.371 (2.21)**	0.175 (1.08)	0.236 (1.91)*	-0.072 (0.36)	0.260 (2.74)***
Trade Secrecy Index†	0.533 (2.53)**	0.789 (1.17)	0.379 (0.62)	0.901 (1.83)*	0.497 (0.68)	0.549 (1.71)*

N = 280. Robust z statistics in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%
†: in logs. #: in intensity form. See section IV for variable definitions. All explanatory variables are lagged values. Regressions also include a constant, the non-manufacturing share of jobs, the share of jobs in all 17 industries, the share of patents in all 17 industries, the share of patents in R&D intensive industries, the ratio of college enrollment to adult population, the percent change in jobs, and 7 BEA region dummies.

Table 3: Negative Binomial Regressions, Continued						
	(7)	(8)	(9)	(10)	(11)	(12)
	Primary Metals	Fab. Metal Products	Machinery	Metal Working Machinery	Computers	Other Machinery
Job Density†	12.236 (2.30)**	-0.563 (0.25)	2.571 (0.88)	4.338 (1.13)	8.978 (1.86)*	1.988 (1.03)
Square of Job Density†	-0.818 (2.29)**	0.042 (0.27)	-0.178 (0.91)	-0.289 (1.11)	-0.597 (1.82)*	-0.139 (1.07)
Jobs†	1.319 (4.29)***	1.220 (9.14)***	1.224 (7.80)***	1.333 (7.20)***	1.764 (6.26)***	1.425 (11.04)***
Square of Jobs†	-0.046 (1.32)	-0.025 (1.44)	-0.027 (1.33)	-0.042 (1.90)*	-0.060 (1.82)*	-0.050 (3.21)***
Industry Share of Jobs	-1.226 (0.34)	7.669 (2.46)**	2.779 (0.66)	18.502 (2.42)**	23.688 (3.74)***	8.621 (2.43)**
Establishments per 100,000 Employees†	0.145 (0.27)	1.586 (7.38)***	1.261 (4.07)***	1.446 (4.29)***	1.878 (3.52)***	1.257 (5.47)***
Manufacturing Specialization (HHI)†	0.374 (2.36)**	0.088 (1.35)	0.298 (3.24)***	0.257 (2.39)**	-0.284 (1.68)*	0.081 (1.15)
Non- Manufacturing Specialization (HHI)†	0.618 (0.81)	0.540 (2.35)**	0.504 (1.43)	0.784 (1.85)*	2.216 (2.91)***	0.650 (2.29)**
Human Capital#	3.268 (1.92)*	2.415 (3.72)***	3.187 (3.99)***	2.170 (2.40)**	2.316 (1.47)	3.022 (4.22)***
Academic R&D#	0.049 (0.63)	0.096 (2.76)***	0.017 (0.44)	0.061 (1.38)	0.165 (2.18)**	0.087 (2.52)**
Government Lab R&D#	0.021 (4.18)***	0.007 (3.16)***	0.001 (0.31)	0.012 (3.31)***	0.003 (0.69)	0.008 (3.82)***
Private R&D#	0.108 (0.60)	0.076 (0.84)	0.168 (1.66)*	-0.056 (0.50)	0.392 (2.17)**	0.222 (2.77)***
Trade Secrecy Index†	2.459 (3.74)***	0.489 (1.78)*	0.380 (1.12)	0.830 (2.21)**	2.225 (3.33)***	0.079 (0.28)

N = 280. Robust z statistics in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%
†: in logs. #: in intensity form. See section IV for variable definitions. All explanatory variables are lagged values. Regressions also include a constant, the non-manufacturing share of jobs, the share of jobs in all 17 industries, the share of patents in all 17 industries, the share of patents in R&D intensive industries, the ratio of college enrollment to adult population, the percent change in jobs, and 7 BEA region dummies.

Table 3: Negative Binominal Regressions, Continued						
	(13)	(14)	(15)	(16)	(17)	(18)
	Electric	Electric2	Comm.	Motor Vehicle	Other Transp Equip.	Instruments
Job Density†	1.844 (0.52)	10.038 (2.86)***	6.771 (2.16)**	-0.990 (0.29)	-1.680 (0.62)	1.543 (0.55)
Square of Job Density†	-0.142 (0.60)	-0.677 (2.85)***	-0.444 (2.11)**	0.054 (0.23)	0.115 (0.63)	-0.099 (0.52)
Jobs†	1.519 (7.02)***	1.170 (5.65)***	1.037 (5.34)***	1.551 (8.02)***	1.137 (6.27)***	1.324 (9.40)***
Square of Jobs†	-0.048 (1.94)*	-0.005 (0.21)	0.012 (0.50)	-0.070 (3.02)***	-0.017 (0.78)	-0.032 (1.88)*
Industry Share of Jobs	-1.801 (0.19)	4.216 (1.27)	3.643 (1.17)	2.633 (1.03)	5.354 (3.40)***	1.533 (0.64)
Establishments per 100,000 Employees†	1.479 (2.94)***	1.103 (3.15)***	1.379 (3.97)***	1.472 (4.01)***	1.878 (4.61)***	1.093 (4.45)***
Manufacturing Specialization (HHI)†	0.137 (0.89)	-0.081 (0.60)	0.044 (0.34)	0.145 (1.29)	-0.107 (0.86)	0.081 (1.01)
Non- Manufacturing Specialization (HHI)†	1.093 (1.81)*	1.203 (2.77)***	0.232 (0.47)	0.990 (2.04)**	0.838 (1.65)*	0.557 (1.93)*
Human Capital#	2.722 (2.39)**	3.865 (3.52)***	2.792 (2.99)***	1.341 (1.52)	1.514 (1.31)	2.469 (3.15)***
Academic R&D#	0.156 (2.55)**	0.086 (1.27)	0.058 (1.08)	0.070 (1.13)	0.111 (1.92)*	0.107 (3.06)***
Government Lab R&D#	0.008 (1.85)*	0.005 (1.13)	0.008 (2.42)**	0.003 (1.18)	0.008 (2.54)**	0.006 (2.95)***
Private R&D#	0.134 (0.97)	0.193 (1.56)	0.248 (2.08)**	0.262 (1.90)*	0.312 (2.59)***	0.258 (2.97)***
Trade Secrecy Index†	0.455 (1.10)	0.625 (1.38)	0.556 (1.35)	-0.406 (0.98)	-0.180 (0.43)	0.226 (0.90)

N = 280. Robust z statistics in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%
†: in logs. #: in intensity form. See section IV for variable definitions. All explanatory variables are lagged values. Regressions also include a constant, the non-manufacturing share of jobs, the share of jobs in all 17 industries, the share of patents in all 17 industries, the share of patents in R&D intensive industries, the ratio of college enrollment to adult population, the percent change in jobs, and 7 BEA region dummies.

Table 4 Optimal Density and Scale and Elasticities for Selected Covariates*								
				Elasticities				
						Specialization (HHI)		
Industry	Optimal Density	Economies of Scale[#]		Industry Job Share	Estabs per 100k Jobs	Mfg.	Non-Mfg.	Secrecy
Total	**2,016**	1.06		**N/A**	**1.27**	0.06	**0.46**	**0.53**
Food	1,492	**1.22**		0.07	**1.27**	**0.34**	-0.33	0.78
Textiles	**1,736**	1.13		**-0.10**	**1.43**	**0.43**	-0.78	0.38
Chemicals	**2,019**	**1.26**		**0.07**	**1.27**	0.03	0.33	**0.90**
Drugs	**1,714**	**1.54**		0.02	0.20	-0.19	**2.03**	0.50
Non-Metal Materials	**1,973**	1.07		**0.14**	**1.40**	0.13	**0.70**	**0.55**
Primary Metals	**1,771**	1.05		-0.01	**0.14**	**0.37**	0.62	**2.46**
Fabricated Metal Products	857	**1.08**		**0.13**	**1.59**	0.08	**0.54**	**0.49**
Machinery	**1,346**	1.07		0.02	**1.26**	**0.30**	0.51	0.38
Metal Working Machinery	**1,820**	1.09		**0.06**	**1.45**	**0.26**	**0.78**	**0.83**
Computers	**1,840**	**1.42**		**0.09**	**1.88**	**-0.28**	**2.22**	**2.22**
Other Machinery	**1,289**	**1.13**		**0.10**	**1.26**	0.08	**0.65**	0.08
Electric	672	**1.24**		-0.01	**1.48**	0.14	**1.09**	0.45
Electric2	**1,665**	**1.14**		0.03	**1.10**	-0.08	**1.20**	0.62
Communication Equipment	**2,042**	**1.11**		0.04	**1.37**	0.04	0.23	0.56
Motor Vehicle	9,707	**1.15**		0.03	**1.47**	0.15	**0.99**	-0.41
Other Transport Equipment	**1,474**	1.04		**0.06**	**1.88**	-0.11	0.84	-0.18
Instruments	2,406	**1.14**		0.01	**1.09**	0.08	**0.56**	0.23

Based on regressions reported in Table 3. See Section IV for variable definitions.
*: bold numbers indicate statistical significance at least at the 10% level of significance.
[#]: evaluated at the mean of city size (jobs) in our data

Table 5: Elasticities*						
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Food	Textiles	Chemicals	Drugs	Non-Metal Materials
Hitech Patents#	**0.155**	**0.192**	**0.152**	0.084	0.134	**0.088**
Human Capital#	**0.592**	0.199	**1.00**	**0.868**	**0.888**	**0.633**
Academic R&D#	**0.071**	**0.106**	**0.078**	**0.129**	**0.188**	**0.041**
Government Lab R&D#	**0.009**	0.009	**0.020**	**0.011**	**0.012**	**0.008**
Private R&D#	**0.077**	**0.113**	0.053	**0.072**	-0.022	**0.078**
Job Growth (%)	**0.210**	**0.155**	0.167	0.098	0.022	**0.227**
	(7)	(8)	(9)	(10)	(11)	(12)
	Primary Metals	Fab. Metal Products	Machinery	Metal Wkg Machinery	Computers	Other Machinery
Hitech Patents#	0.024	**0.075**	**0.083**	**0.192**	0.105	**0.104**
Human Capital#	**0.639**	**0.472**	**0.623**	**0.424**	0.453	**0.591**
Academic R&D#	0.027	**0.054**	0.010	0.034	**0.093**	**0.049**
Government Lab R&D#	**0.030**	**0.010**	0.001	**0.017**	0.005	**0.011**
Private R&D#	0.033	0.023	**0.051**	-0.017	**0.119**	**0.068**
Job Growth (%)	**0.434**	**0.192**	**0.222**	**0.177**	**0.336**	**0.155**
	(13)	(14)	(15)	(16)	(17)	(18)
	Electrical Equipment	Electrical Equipment 2	Comm. Equipment	Motor Vehicles	Other Trans. Equipment	Instruments
Hitech Patents#	**0.128**	-0.048	**0.126**	0.116	0.032	**0.090**
Human Capital#	**0.532**	**0.755**	**0.545**	0.262	0.296	**0.483**
Academic R&D#	**0.088**	0.048	0.032	0.004	**0.062**	**0.060**
Government Lab R&D#	**0.011**	0.006	**0.011**	0.005	**0.012**	**0.009**
Private R&D#	0.041	0.059	**0.075**	**0.080**	**0.095**	**0.078**
Job Growth (%)	**0.360**	**0.221**	**0.314**	**0.359**	**0.305**	**0.227**

Based on regressions reported in Table 3. See Section IV for variable definitions.
*: Bold numbers indicate statistical significance at least at the 10% level of significance.
#: in intensity form.