Title
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By

Stephen Malpezzi

May 2001

These papers are preliminary in nature: their purpose is to stimulate discussion and comment. Therefore, they are not to be cited or quoted in any publication without the express permission of the author.
NIMBYs and Knowledge:
Urban Regulation and the "New Economy"

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This paper is highly preliminary and will be revised. Comments and criticisms are particularly welcome. Please contact me for a copy of the revised version of the paper.

Opinions in this paper are those of the author, and emphatically do not reflect the views of any institution.
1. Introduction

The purpose of this paper is to explore possible relationships between certain aspects of what used to be called the “New Economy,” in particular the economic structure of a metropolitan area, and some aspects of the housing market, namely NIMBYism and land use regulation; housing prices, and urban form (“sprawl”).

If we took the time to fully discuss what is meant by the "New Economy," or the "Next Economy," or the "Knowledge Economy," we'd quickly use up most of the pages even the most patient reader would plow through. So from this point on, we’ll be deliberately fuzzy; we’ll use the term “High Tech,” dropping the quotes, to loosely characterize localities (metropolitan areas, in this paper) that have above-average shares of their economy devoted to activities that have (or are thought to have) high technology content (whatever that means). Of course, when we use specific measures of “tech-ness,” we’ll describe these more fully, but there is no consensus on exactly what this term means or how to operationalize it. We will try to examine several alternative measures, to see if any of our refractory findings are robust.

This paper is also largely discursive and descriptive. Some plots and even some multiple regressions are presented, but we have yet to develop formal models of the phenomena we're examining. Consider the paper as an exercise in exploratory data analysis. In this fairly loose way, we examine the following questions:

(1) Are High Tech locations (metro areas) systematically growing and developing faster than the rest of the country? For that matter, how important is industrial structure generally as a predictor of development?

(2) Are High Tech metro areas characterized by more stringent development regulation than other areas?

(3) Do High Tech locations have systematically higher housing prices than the rest of the country? Can we disentangle the effects of faster growth, regulation, and other determinants?

(4) Are High Tech locations systematically more decentralized or “spawling” than other metropolitan areas?

The plan of the paper, roughly following our four questions, is as follows. In section two, we will briefly discuss some measurement issues, regarding first NIMBYism, or more specifically, its manifestation, development regulation; and secondly, the "high-tech-ness" of a local economy. Next, we will examine whether High Tech regions are in fact growing faster. The fourth section explains the relationship between NIMBYism and High Tech, and growth generally. The fifth section explains the relationship between these phenomena and house prices. Finally, we present some initial evidence on the relationship between the structure of the local economy and urban form.

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1 "Used to?" How quickly fads come and go, whether we’re talking pop jargon or NASDAQ bubbles. Don Nichols (among others?) has argued for the term “Next Economy.”
2. Measurement Issues

Measuring "High Tech" in the Localized New Economy

In this paper we explore three alternative measures of "High Tech," due to DeVol (1999), Malecki (1981) and Zacks (2000). But before we dive into the measures, let us briefly consider the role technology plays in the economy generally, and in local economies (metro areas) specifically.

At one level, there can be hardly any doubt that technology affects development. The early development of cities ten thousand years ago was tied to technological improvements in agriculture that permitted at least a few members of society to engage in activities other than gathering enough calories to stay alive. Many studies have explored the role of such technical innovations as the steam engine, electricity, and railroads in the history of economic development in the United States.

Adams and Sveikauskas (1993) demonstrate the linkages between academic science, applied research and development, and economic development. Among other measures, they use the number of industry scientists as a measure of R&D and academic papers as crude measures of scientific output. Their findings demonstrate that first science and at a later stage R&D "are a powerful mover of the entire structural production … and they appear to be a potent force responsible for capital deepening in the U.S. and other economies." Other studies such as Jaffe (1989), Beeson and Montgomery (1993), and Felsenstein (1996) demonstrate the positive impacts of universities and academic research on economic development.

There are many debates in the literature today about just exactly what role current improvements in information technology, medical capabilities, biotechnology and the like have on economic development.\(^2\) A number of studies have suggested surprisingly weak relationships between this technology and economic growth in the aggregate; but many other studies suggest that this is partly a data problem (productivity growth and services, now the dominant sector of the economy, is hard to measure). Furthermore, it takes time for new inventions to become sufficiently disseminated that an impact is discernible on economic growth. This period of innovation was actually quite long even for older technologies like the steam engine; many authors believe that we are only now beginning to see the real productivity gains from the computer revolution of ten to fifteen years ago.

We can also distinguish between the effects of technology in the aggregate economy and its localized effect. In other words, a bio-technological or electronic innovation in, say, Madison Wisconsin will, over time, benefit the entire U.S. economy and presumably the world. How much of this benefit is at least initially captured locally?

In principle, it is quite possible to imagine a world in which technology benefits the overall economy without differentially benefiting some locations. But of course we know that different regions, even the largest MSAs, specialize in some kinds of production (Henderson 1974, 1988). In High Tech, the much-remarked upon development of Silicon Valley (and its imitators, Silicon Fen, etc.), Route 128, Bangalore’s IT cluster, and so on, confirm the importance of agglomeration economies in general and in high tech. This is in marked contrast to the "Death

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\(^2\) See, for example, Gordon (2000), Jorgenson and Stiroh (1999), Nichols (2000).
of Distance” point of view that says advances in information technology are making location unimportant.3

Part of the problem is probably due to how we define "high tech," usually based on the perceived qualities of an industry's output, rather than the nature of the production process or the business model. For example, a janitor working in the semiconductor industry is counted as "high tech," while a software engineer working for a paper company is counted as "low tech." Increasingly, students of economic development are catching on to the fact that our labels of "high tech" and "the New Economy," as commonly used, often obscure more than they enlighten.

Our first measure of the "high tech-ness" of a local area, specifically MSA, comes from a Miliken Institute study. DeVol (1999) and colleagues calculated the location quotient of a number of high tech industries and services, including bio-technology, electronics, medical services, aeronautics, and the like. They used three digit SIC code data on employment to choose "industries that spend an above-average amount of revenue on R&D and that employ an above-average number of technology-using occupations."4 The basic data location quotient data we use in this paper come from 1990.

DeVol's high tech LQ is available for most (315) metropolitan areas. The MSAs with the highest "tech value" are Rochester, MN (5.5), San Jose (4.1), Albuquerque (3.1), Lubbock (3.1), and Cedar Rapids (3.1). Other notable MSAs with LQs greater than 1.3 include Seattle, Boston, Denver, San Diego, Atlanta, Los Angeles, and Austin. Many small metro areas have very low high tech LQs, often below 0.05. Among the large MSAs with LQs below 0.7 are Cleveland, Syracuse, Buffalo, Las Vegas, Cincinnati, Detroit and Milwaukee.

Our second measure comes from a somewhat older paper by Malecki (1981). Malecki constructed location quotients for federal and for private R&D funding, circa 1977. Raw data came from the National Academy of Sciences, the National Academy of Engineering, NASA, and the National Science Foundation.

We obtained these indexes for 50 large MSAs from Castells (19xx). MSAs with high values of the federal R&D LQ include Melbourne (5.3), Santa Barbara (5.1), Seattle (3.0), Los Angeles (2.8), and Binghamton (2.8). MSAs with low values of the federal index (less than 0.1) include Pittsburgh, Cleveland, Cincinnati, Chicago, Miami and Milwaukee.

Unsurprisingly, Malecki's results for private R&D are quite different than for federal. In particular, private R&D is less concentrated than federal, so that the largest private LQs are smaller than their corresponding federal indexes, and the smallest private LQs are larger than their federal counterparts. The correlation between federal and private LQs is only 0.19, which is small enough that the probability is roughly one in five it's due to chance. The largest public indexes are Santa Barbara (1.8), Cleveland (1.8), Nashua (1.8), Boston (1.7) and Washington, DC (1.6). The lowest MSAs are Biloxi, Miami, Tampa, New Orleans and Orlando, all below 0.26.

Our third measure comes from an article in MIT's Technology Review by Zacks (2000). Raw data, primarily patent based, was provided by CHI Research, and the Association of University Technology Managers. Zacks provided a variety of measures for the top 50 (by her measures) research universities in the United States. The measure we focus on is an "impact

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3 See Cairncross (1997) for arguments pro the "death of distance." See Kolko (1997) for evidence that distance is not dead yet.

4 Devol (1999) page 34, provides a detailed explanation of their definitions.
index” of patents from each university, which is weighted by the number of citations of a patent in other patent applications. To match up this data with our other sources, I attributed each university's score to the metropolitan area in which the university is located.

The top 10 scores in Zacks' index, in order, are: San Francisco, Boston, Raleigh, Los Angeles, Austin, San Jose, Baltimore, Philadelphia, New York and Madison. Since this is an index of the top 50 research universities, not originally MSA based, there are a number of small MSAs with major research universities like Madison, Ann Arbor, Beaver County (Penn State), and Iowa City near the top. Among the many large MSAs that don't make the cut for a score, some considered fairly techy by other criteria, are Chicago, Houston, Detroit, Dallas, Denver, and Milwaukee.

Table 1 presents the simple pairwise correlations of these indices. We have already noted the low correlation between Malecki’s federal and private indexes. Note the negative correlation between Zacks' patent based index, and the others (although it's really zero vis a vis the Malecki indexes; it is negative vis a vis the DeVol index). In general the correlations among these measures are usually quite small; our initial reaction is that it will be difficult to develop a good measure of "High Tech" that is robust and valid. In most of what follows, we'll focus on DeVol's measure, since it's fairly recent, comprehensive, and cited in other recent research. We'll also construct a dummy variable for the "top 10" MSAs vis a vis the Zacks index.

Measuring NIMBYism: The Stringency of Regulation

NIMBYism is an attitude, and attitudes are hard to measure. I don't know of any systematic data on attitudes of the general populace towards housing development by metropolitan area, but there is some data on the most directly observable NIMBY outcome: the stringency of housing and development regulation. Several papers have attempted to measure "regulation" across U.S. markets, and a few of these have examined the effects of regulation on land and housing prices. Malpezzi (1996) presents a summary. Segal and Srinavisan (1985), for example, surveyed planning officials and collected their estimates of the percentage of undeveloped land in each MSA rendered undevelopable by land use regulations. Using a regression model of house price determinants, they found that as the percentage of developable land removed by regulation increased, so did house prices.

Black and Hoben (1985) developed a categorization of MSAs as restrictive, "normal", or permissive, based on a survey questionnaire from planning officials. They found a simple correlation of -.7 between their index and 1980 prices for developable lots. Chambers and Diamond (1988) used data from the ULI survey in a supply and demand model for land prices. They characterized their results as mixed. For example, in their equation explaining 1985 land prices, average time of development project approval had a positive and significant effect on land prices, but negative and insignificant effect in the 1980 regressions. In another paper using the ULI data, Guidry et al. (1991) found that the average 1990 lot price in their 15 “least restrictive” cities was $23,842 but that in the 11 ”most restrictive” cities the average was $50,659.

Rose (1989a,b) constructed an index which measured land removed from development by natural constraint, and in Rose (1989b) used the number of governments a la Hamilton (1978) as a proxy for regulatory constraint. He found that the natural and contrived restrictions explained about 40 percent of variation in land prices; about 3/4 of this was due to natural restriction and about 1/4 apparently due to regulation.
Malpezzi (1996) estimates the costs and benefits of development regulation. The benefit side was examined using reduced form models for several measures representing possible benefits of regulation (or, given perverse signs, further costs): homeownership rates, congestion, racial segregation, and neighborhood quality ratings. The results suggested that, past some threshold, rents and house values were driven up by more stringent regulation; that homeownership rates were lowered, primarily because regulation causes asset prices to increase faster than rents; and that congestion was modestly lower, *ceteris paribus*, in more heavily regulated cities.

The Malpezzi (1996) regulatory index was constructed using raw data collected by Linneman and Summers (1990, see also Buist 1991). The index comprised data on:

1. The change in approval time (zoning and subdivision) for single family projects between 1983 and 1988.
2. The estimated number of months between application for rezoning and issuance of permit for a residential subdivision less than 50 units.
3. A variable similar to (2), but based on the time for single family subdivision greater than 50 units.
4. A qualitative assessment of how the acreage of land zoned for single family compares to demand.
5. The amount of acreage of land zoned for multifamily compared to demand for multifamily.
6. The percentage of zoning changes approved.
7. The adequacy of infrastructure (roads and sewers).

Figure 1 presents a plot of housing prices against one of the regulatory variables constructed from this information by Malpezzi (1996). The lowest possible score is 7 (least stringent regime), and the highest 35 (most stringent). Chicago had the lowest value of REGTEST, 13, while San Francisco and Honolulu had values of 29.

Figure 1 clearly shows the relationship between regulation and housing prices, particularly once an MSA exceeds a threshold value of about 22 or so. Malpezzi (1996) shows that this relationship remains even once demand side conditions, and geographical supply side constraints are controlled for. Malpezzi Chun and Green (1998) shows that this relationship holds once the possible endogeneity of the regulatory measure is controlled for. Malpezzi (1999) shows the effect regulation has on price dynamics, increasing the equilibrium price, and slowing the time path of adjustment to equilibrium. Green, Malpezzi and Mayo (2000) demonstrate that supply elasticities are lower in heavily regulated MSAs.

The determinants of regulation have been understudied. Cooley and LaCivita (1982) presents a theoretical model which explains how the demand for controls can arise because of, e.g., congestion and fiscal externalities. Few empirical tests of such models have been carried out as yet. Most of the regulatory studies cited in the preceding section, such as Segal and Srinavisan (1985), Black and Hoben (1985), Rose (1989 a, b) and Malpezzi (1996) treat regulation as exogenous.
Rolleston (1987) develops a simultaneous model of the decision to develop and the decision to zone. The model is estimated recursively using municipal zoning data from northeastern New Jersey. Among other results, Rolleston finds the restrictiveness of residential zoning is positively related to the relative fiscal position of a locality, and negatively related to the size of minority population. Several variables were contrary to expectations; for example, increased income dispersion, and proximity to employment, were positively related to the restrictiveness of zoning.

Gin and Sandy (1994) estimate the demand for residential growth controls using zip code level voting results from a San Diego County voter initiative on controls. Higher rates of homeownership, and of population growth, are associated with stronger votes for controls. Larger minority populations, and higher incomes are associated with weaker support for controls; the latter is contrary to expectations.

Several other papers have focused on the role population growth plays in the adoption of controls. It seems reasonable that stronger growth could lead to demand for more stringent controls, as Gin and Sandy found. But the literature is not robust. Logan and Zhou (1990), for example, find that past growth is not related to demand for controls in a national sample of suburban municipalities.

Lenon, Chattopadhyay and Heffley (1996) develop a model which emphasizes the fiscal interdependencies of neighboring jurisdictions, and estimate it using data from Connecticut townships. They find that, indeed, each town's zoning, taxing and spending policies are strongly related to those of neighboring towns.

One of our own studies sheds a little light on this subject. In this paper we use an instrumental variable version of the regulatory index, described in detail in Malpezzi, Chun and Green (1998):

\[ R_i = Z_i G + ?_i \]

where \( R \) represents the original Malpezzi (1996) regulatory index, \( Z \) is a vector of exogenous determinants of \( R \), \( G \) is a corresponding vector of coefficients, and \( ? \) is an error term. In addition to the econometric aim of purging the regulatory index of errors correlated with housing prices, in this particular case the procedure also provides us with indexes for a much larger sample of metropolitan areas (272 versus the original 56).

MCG used the size of the MSA, its income, crowding, population growth, housing tenure, physical geography, and several locational dummies for unusual environments as instruments. In the IV construction, MSAs with higher incomes have stronger regulatory environments; and larger MSAs have less stringent regulation; but given the large standard errors, there is more than one chance in ten a t-statistic could be observed under the null. Growth in population, household crowding, and a measure of natural constraint (adjacent to a large park, military or Indian reservation) are far from any standard level of significance. Demographics clearly do matter. Demographics are captured with the percentage of households whose head is aged 65 or older; there is only a one in forty chance of observing a t-statistic this large under the null. Markets with a high degree of owner occupants in 1980 are less likely to have stringent regulation, and the effect is significant. The performance of the locational dummy variables was mixed. The California dummy was positive and significant. But the dummy variable for New York, and that for Honolulu were not. The California result suggests that state is indeed different.
and is consistent with Fischel's (1995) argument about that state's particular brand of regulatory and judicial activism.

3. Are High Tech Regions Growing Faster?

It appears so. Figure 2 shows the fairly modest correlation between DeVol's high tech location quotient and subsequent growth in real per capita income in each MSA. The correlation coefficient between DeVol's index and this income growth is 0.14, and between the LQ and employment growth is 0.10.

Table 2 presents some "naive" regressions exploring a few determinants of growth. Notice that employment growth is faster in high tech metro areas, even after controlling for size, and initial income. More specifically, the DeVol LQ is positive and statistically significant; but the dummy for MSAs in Zacks' top 10 patent citations is insignificant. Metro areas with higher fractions of elderly are growing more slowly.

NIMBYism's Effects on High Tech, and on Growth

Perhaps most interestingly, markets with more stringent regulatory environments are growing more slowly. Why? Malpezzi (2001) presents preliminary evidence that higher housing prices slow down growth; and of course more stringent regulations raise housing prices.

Still, the effect of the DeVol index is modest. This may seem paradoxical, but it does not mean high tech is not important. It simply points out what we already know: that different metropolitan areas have different comparative advantages based on their resources, human capital, location, agglomeration economies, and the like. For some locations, high tech will be extremely important; no one believes that the San Jose metropolitan area would have grown nearly as fast as it has without the Silicon Valley. But on the other hand, there are many paths to economic development, and other metropolitan areas can grow through decidedly low tech development paths, for example, tourism, educational services (paradoxically, not always a terribly high tech industry), and the like.

In other literature, even the generally accepted aggregate relationship between technology and growth occasionally comes under fire, especially with respect to recent advances in information technology. Examples of studies that have found no effect or even negative effects of information technology on the growth of particular industries include studies of the financial sector by Franke (1987) and Weill (1992). However, recent studies by Brynjolfsson (1993) and Stolarick (1999) have found positive relationships between information technology investment and productivity. Stolarick in particular finds that the effects of information technology varied markedly among industrial sectors, in a way that probably explains many of the null results previously found in the literature.

The bottom line seems to be: there is no doubt that technology matters in the aggregate, in the long run. But the case for encouraging high-tech development must be more carefully made, as developing such clusters effectively depends on a host of preconditions, including the presence of a strong research environment.
“High Tech,” Regulation and Housing Markets
(to be added)

The Structure Of The Local Economy And Urban Form
(to be added)
References


Kolko, Jed. The Death of Cities? The Death of Distance? Evidence from the Geography of Commercial Internet Usage. Harvard University, Processed, 1999.


House Prices & Regulation

Median House Value, 1990 Census ( Thousands )

MSA-Specific Regulatory Index

San Francisco (SF)
Chicago (CHI)
Los Angeles (LA)
Philadelphia (PHL)
Houston (HOU)
Dallas (DAL)
San Diego (SD)
Phoenix (PHX)
Bal Harbor (BAL)
Indianapolis (IND)
San Jose (SJS)
Cleveland (CLE)
New York (NY)

House Prices & Regulation
Growth in MSA Real Income Per Capita, and High Tech
Table 1: Pearson Correlations Between "Tech" Measures, Regulatory Indices

<table>
<thead>
<tr>
<th></th>
<th>DeVol Hi Tech LQ</th>
<th>Malecki Federal R&amp;D LQ</th>
<th>Malecki Private R&amp;D LQ</th>
<th>Zacks Patent Citation Index</th>
<th>Malpezz Development Regulation Index</th>
<th>MCG Instrumental Variable Regulation Index</th>
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<tr>
<td><strong>Cor</strong></td>
<td>1.00</td>
<td>0.38</td>
<td>0.04</td>
<td>-0.51</td>
<td>0.21</td>
<td>-0.01</td>
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<td>**Prob</td>
<td>r</td>
<td>**</td>
<td></td>
<td>0.0079</td>
<td>0.7708</td>
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<tr>
<td><strong>N</strong></td>
<td>315</td>
<td>48</td>
<td>48</td>
<td>41</td>
<td>56</td>
<td>272</td>
</tr>
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</table>

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For each correlation, the table lists the correlation coefficient (Cor), the probability value (Prob |r|), and the sample size (N). The table indicates the strength and direction of the relationship between the variables, with correlation coefficients ranging from -1 to 1. Positive values indicate a positive correlation, while negative values indicate a negative correlation. Prob |r| values less than 0.05 are considered statistically significant, suggesting a strong relationship between the variables. The N values reflect the sample size for each correlation analysis.
Table 2: Naive Regression Models of Recent MSA Employment and Income Growth

(Preliminary, do not cite).

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Annual Growth in PC Income, 90-98</th>
<th>Annual Growth in Employment, 90-98</th>
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<td>Income Per Capita, 1990</td>
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<td>5.48E-06</td>
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<td>Log MSA Population, 1990</td>
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