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Specialization and Regional Economic Development

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Abstract
Debates about urban growth and change often center on specialization.However, arguments linking specialization to metropolitan economic development contain diverse, and sometimes conflicting, claims. Is it better to be highly specialized or diversified? Does specialization refer to the absolute scale of an activity in a region, its share within the regional economy, or its share in the nation's economy? Does specialization have static effects, or is its impact chiefly evolutionary? This paper starts by investigating these different theoretical claims. We then turn to an empirical inquiry into the roles of relative and absolute specialization. By analyzing local agglomerations over time, we find that growing absolute specialization is positively linked to wages, while changes in relative concentration are not significantly associated with wage dynamics. This supports notions of specialization based on the absolute size of an agglomeration, and casts doubt on notions of specialization based on shares of an activity in the regional economy.

JEL Classifications: R11; R12; O21
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1. Introduction: The Fascination with Specialization

Discussions of urban growth and change often center on specialization. Urban planners, economic development authorities, consultancies and private businesses want to know about the prospects of metropolitan economies, and a principal way they do this is by assigning some kind of causality to patterns of industrial activity in the region. We often hear cities and metropolitan areas described in terms of their iconic activities, such as finance, high tech, logistics, services, or labor-intensive manufacturing. And such labels carry implicit value judgments. In recent years, membership in the global club of the richest metropolitan economies is strongly associated with regions that are centers of information technology and capitals of finance. In developed countries, big manufacturing regions are in decline, in terms of their income rank and often in their population, while in the developing world, hubs of export-oriented labor-intensive manufacturing, such as Guangzhou, are said to have the secret to growth. Specialization is a principal way, then, that urban economies are viewed, labeled and classified by practitioners and policymakers, and it defines the public imagination about specific cities.

Specialization also features prominently in academic debates over economic development. Specialization and its flip side, diversification, are notions that apply to the tradable part of any economy; but the majority of any economy – regional or even national – consists of the production of non-tradable goods and services. What the economy does in the tradable sector, however, has strong effects on the overall level of regional employment and income. The tradable sector generates income that is spent on non-tradables in its "home market." The wages that are established in the tradable sector thus can influence wages in the firms and industries producing for the home market in a variety of ways. The level of regional income is strongly influenced by specialization because a regional economy's external terms of trade[1] are set by its tradable sector, and its overall level of output is influenced by tradables because demand for them is not limited by the producing region's income. A favorable specialization pattern (terms of trade and growth of external demand) is clearly good for the economy of the region. Evidence for the U.S. is suggestive: the bulk of national income growth between 1994 and 2000 was driven by large gains in just five of the country's 3,141 counties: Santa Clara, CA; San Mateo, CA, San Francisco, CA; King, WA; and Manhattan, NY – iconic specializations of information technology and financial services (Galbraith and Hale, 2004).

When we look more closely, however, academic arguments linking specialization to metropolitan economic performance contain many different, and sometimes conflicting, claims. Is it better to have your regional economy be highly specialized or diversified? Does specialization refer to the absolute scale of an activity in a region, its share in the overall regional economy, or its share in the nation's economy? Does specialization have positive or negative effects in a static way (augmenting productivity or improving the terms of trade, for example), or by somehow affecting the regional economy's development over time?

It is difficult to come by hard evidence on how levels and types of specialization affect employment and income. And this is not surprising, because it is difficult to measure specialization in a way that captures all the dimensions referred to above, notably by integrating absolute and relative measures in a single index. Moreover, there is a problem of aggregation or granularity: at what level should we define the activities that are similar, and where should we draw the borderline between activities that are different? This is both a conceptual problem and a challenge given the data available to analysts.

[1] For the present purposes, "terms of trade" refers to the relative prices of the region's output compared to the prices of the goods and services it imports. If the region's output enjoys increasing ratios of its unit prices relative to what it imports, then its terms of trade are said to be improving.

In this paper, we examine the link between specialization and economic development in a number of ways, in order to shed some light on these issues and make some progress in assessing how specialization and regional economic development might be related. In sections 2 and 3 we explore how specialization gets defined in the academic and popular debates, and discuss how these definitions might relate to economic development. Section 4 illustrates how measurement issues shape our perceptions of specialization. The core of the paper is an empirical test of the relationship between specialization and economic performance in U.S. metropolitan areas (section 5). In Section 6 we conclude with words of caution about the uses of specialization in both academic and policy debates.

2. Specialization or Diversification?

In economic development circles, it has long been debated whether it is better for an economy to be diversified or highly specialized (Hoover, 1948; Richardson, 1968; Quigley, 1998; Beaudry and Schiffauerova, 2009). We can define a diversified region as one that contains a wide array of unrelated sectors in its economic base, with no specific sector dominating. As we shall see, translating such conceptual notions into precise empirical guidelines is quite complicated, but for the moment let us stick to the conceptual level.

Three justifications have been advanced for the virtues of diversification. The most common, for economic development professionals and some academics, is that diversification spreads the risk from economic fluctuations; this is the virtue of not putting all one's eggs in the same basket. Just as diversifying an individual's investment portfolio buffers against the volatility inherent in any single company's performance, so does the diversification of regional specialization hedge against ups and downs in individual sectors (Attaran, 1986; Koren and Tenereyro, 2003).

While the argument is intuitively appealing, it has two major weaknesses. First, since it is principally addressed to offsetting negative shocks, it does not adequately consider whether being highly diversified causes an economy to forego developmental opportunities on the up side. In other words, it does not consider whether diversification has opportunity costs, depriving an economy of benefits that could come from capturing growing sectors.To our knowledge, there exists no robust evidence to suggest that the effects of diversity go beyond volatility to determine long-term patterns of employment, whether positively or negatively.

Second, the effects of diversification are likely to be sensitive to size. For example, in a small, diversified economy, the collapse of demand in a single tradable sector might have a minor absolute effect on the local economy, but could have a large impact on non-tradables (decline in demand), if those are already producing at scales that are at the lower range of feasibility. In a large, diversified economy, even if the collapse of demand for an activity has a larger absolute impact, it might affect the local non-tradable sector less, because local non-tradables are probably operating at higher scales on average than in a small regional economy. Our hunch is that diversification is unlikely to have a clear independent relationship to the quantity or volatility of employment, and that in any case, there is great likelihood of reverse causality. Moreover, this argument seems to concern the quantity of employment, rather than its quality. It is hard to see how diversification would directly lead to better economic performance, in terms of augmenting productivity or incomes.

A second, subtler argument for diversification holds that urbanization economies supply general inputs at efficient scales that are useful to many activities in a region. Therefore, a big metropolitan economy has reason to be diversified, and this will be reflected in its average total productivity relative to smaller regions. The major problem with this argument is obvious: diversification would be an outcome, not a cause of any such performance benefit. Another doubt comes from the nature of factor services supplied by urbanization economies: roads, infrastructure, and such, are the most general types of input to a modern economy. Beyond them, sectors need different and specific inputs (capital, labor, knowledge, supply chains). Urbanization economies do not provide these at the right scale; localization economies do, and localization economies are a force not for diversification, but for specialization.

A third argument for diversification concerns the dynamics of the regional economy. The idea here would be that a modern economy is a vast and very complex social division of labor. For an economy to move into, or capture, new activities, it needs to be able to draw quickly and easily from a shifting set of inputs and factors. This is a kind of "mix and match" view of the dynamics of economic development. A diversified economy might be able to do this better than a highly specialized one.

This is an idea that emerges repeatedly in discussions of economic development, with a recently prominent form touting the virtues of economic "complexity" (Hidalgo and Hausmann, 2009). It also finds echoes in Jane Jacobs' (1969) canonical pronouncements about the virtues of diversification. Upon closer examination, though, it is difficult to pin down its precise meaning. Do economies really develop better over time, again in terms of raised productivity and employment, by mixing and recombining inputs from highly unrelated sectors? Or, if they develop better over time through recombination (Weitzman, 1998), are they actually recombining inputs from sectors that are related, or at least close neighbors in terms of technology and underlying knowledge base? The answer to this question is very sensitive to the categories used for measurement, in other words – the same reality can be spun as a virtue of specialization (relatedness) or diversification.

Attempts to operationalize this idea in empirical terms also suffer from a serious endogeneity problem. Economic geographers have recently argued that an region's long-run economic prospects are sunniest when its industrial structure spans many distinct, but related product spaces (Frenken et al, 2007). Unfortunately, this approach cannot tell us whether this situation is a cause or an outcome of being previously diversified, and thus cannot tell us whether it was better in the past to be specialized in order to subsequently capture a wider range of economic activities. The idea that specialization leads to a more complex industrial structure was suggested by Gunnar Myrdal (1956), and it has been revived in the New Economic Geography's core-periphery model, which demonstrates how an economy that starts with successful specialization gets big and diversifies as a result of its economies of scale in consumption (its home market).

Moreover, any argument about diversification-as-relatedness that leads to better evolution has to deal with the thorny issue of trade costs: in a world where the costs of linking intermediate inputs to outputs is declining, why do we need to be locally diversified, if we can just import what we need from afar? Diversification would have to be useful in the restricted set of conditions whereby: (a) we are better off being able to mix-and-match; and (b), what we need to mix-and-match has to be close by, because it has high trade costs or high usage (know-how, experience) costs or (c), a time constraint that rules out procurement from far away. This doesn't sound like a meaningful definition of diversification as being about combining unrelated activities, but once again like a definition of the virtues of some kind of complex specialization. We have come full circle.

A pragmatic place to begin evaluating the relationship between diversification and economic performance is to compare diversification levels among regional economies. If differences in diversification are considerable, then it may be worth exploring how such variation relates to economic outcomes. To get a back-of-the-envelope gauge of diversification in U.S. regional economies, we take data from the U.S. Census Bureau's *County Business Patterns*, and use it to calculate Herfindahl indices of concentration. A Herfindahl index describes the extent to which a set of observations departs from a uniform distribution. In this case, we describe the distribution of regional specialization in metropolitan areas, with values approaching zero indicating regions that are more highly diversified. To provide some historical sense, we calculate such indices for 2009 as well as 1970. The most detailed industrial data is used in each case: four-digit Standard Industrial Classification (SIC) codes for 1970, and six-digit North American Industrial Classification System (NAICS) codes for 2009.[2]

Table 1: Regional Specialization and Selected Development Indicators for Major Combined Statistical Areas

	1970		2009		1970-2009	
	Specialization (Herfindahl)	Per Capita Income	Specialization (Herfindahl)	Per Capita Income	Income CAGR	Employment CAGR
Atlanta	0.01	$3,932	0.015	$37,101	5.92	4.26
Boston	0.008	4,430	0.015	48,831	6.35	0.89
Chicago	0.004	4,861	0.013	43,047	5.75	0.66
Dallas	0.009	4,167	0.014	39,811	5.96	2.67
Houston	0.009	4,131	0.015	42,523	6.16	2.78
Los Angeles	0.003	4,857	0.012	39,301	5.51	1.52
New York	0.006	5,212	0.013	52,354	6.09	0.47
Philadelphia	0.008	4,458	0.014	44,905	6.1	0.63
San Francisco	0.008	5,265	0.015	54,062	6.15	1.44
Washington DC	0.011	4,802	0.016	52,646	6.33	1.62
U.S. Average	0.027	3,711	0.022	35,763	5.992	1.532
U.S. Std. Dev	0.03	616	0.009	5,311	0.322	0.980

Note: Herfindahl indices produced using County Business Patterns. Larger numbers indicate that sectoral employment patterns deviate from a uniform distribution. Results are not directly comparable across years due to the switch in classification schemes in 1997 from SIC (4-digit) to NAICS (6-digit). SD indicates standard deviation for all U.S. metropolitan areas. Selected development indicators from the Bureau of Economic Affairs Regional Economic Accounts. CAGR stands for compound annual growth rate. Income figures are presented in nominal U.S. dollars. Employment figures exclude proprietors.

Table 1 presents these regional specialization metrics for major metropolitan areas, and complements these with selected indicators of economic development: levels and compound annual grow rates for per capita personal income, as well as employment growth rates. The results show that specialization levels for U.S. metro areas in 1970 are distributed

[2]Acknowledging all the limitations of the industrial data that we discuss in more detail below.

in a fairly narrow arc, both in major cities as well as the overall average across all U.S. consolidated statistical areas. The largest regional economies are, of course, more diversified than the overall distribution of cities, but there is scant variation among large cities. Differences are even narrower in 2009. And yet the economies of these cities varied widely in terms of income levels, and growth rates of population and income. To take one example, Atlanta was the most diversified selected cities, while Los Angeles was the second most diversified. Los Angeles was nearly a quarter richer than Atlanta in 1970; since that time, Atlanta has nearly caught to Los Angeles in terms of income levels, and its employment growth has dramatically outstripped that of Los Angeles. Meanwhile, San Francisco was much more highly specialized in 1970; its income grew considerably faster than both economies, while its employment base grew slower than both. And diversification levels in San Francisco, Atlanta and Los Angeles converge to quite similar levels by 2009. Given the narrow spread of specialization values among metropolitan areas whose economies have performed quite differently, we may want to question the importance of the overall level of specialization or diversity as an influence on development.

3. Relative and Absolute Specialization

Specialization is a term used to signify many different things, and its intended meaning is not always clearly articulated. When making claims about specialization such as "New York is highly specialized in financial services," or "Austin is ranked as the fourth most specialized U.S. metropolitan area in information technology," the vast majority of reports and media buzz are referring to an industry's employment share in the metropolitan economy. This is what we will call "relative" specialization. But specialization can also be thought of in absolute terms: having a particular activity be the source of many jobs, or a high level of output, or large number of firms.

It is impossible to simultaneously rank cities according to these two criteria. A small metropolitan area whose local employment base is dominated by work in a particular activity would rank higher in specialization than a large metropolitan area with a low share but a much higher absolute level of employment or output; the same is true in reverse. Absolute and relative concepts of specialization, then, provide very different images of the economy.

In Table 2 we rank U.S. metropolitan areas according to their relative and absolute specializations in a particular set of activities. For exposition, we focus on information technology, but any tradable sector would do. To minimize the importance of smaller metropolitan areas, we present results only for metropolitan and combined statistical areas with a total employment base over 500,000. The left panels of Table 2 rank regional economies according to the relative importance of employment in a set of 43 six-digit sectors that, consensus agrees, broadly cover the range of information technology activities.[3] The right panels rank cities according to their absolute specialization in these same sectors, that is, on the basis of the actual number of workers they employ.

[3] This definition corresponds to those commonly used by such organizations as the Silicon Valley Index (2008), as well as by Saxenian (1994).

Table 2. Relative and Absolute Specialization in Employment in Information Technology among U.S. Metropolitan (and Combined Statistical) Areas, 2010

Metro Area	Relative		Absolute
San Francisco, CA	10%	San Francisco, CA	255,334
WashingtonDC-MD-VA-WV	8	Washington, DC-MD-VA-WV	240,721
Seattle, WA	7	New York, NY-NJ-CT-PA	184,917
Austin, TX	7	Los Angeles, CA	153,524
Boston, MA-NH-ME-CT	5	Boston, MA-NH-ME-CT	122,474
Atlanta, GA	5	Seattle, WA	90,511
San Diego, CA	5	Dallas, TX	85,989
Dallas, TX	4	Chicago, IL-IN-WI	82,549
Portland, OR-WA	4	Atlanta, GA	74,566
Denver, CO	4	Philadelphia, PA-NJ-DE-MD	52,871

Note: Authors' calculations using employment data from County Business Patterns. To filter out small metropolitan areas, we present results for cities with an employment base over 500,000. For a full list of the six-digit sectors that we define as the IT agglomeration, see Appendix A.

In the relative specialization column, which also corresponds to the ranks assigned on the basis of location quotients, we see a list that conforms to popular IT lore. We find San Francisco and Silicon Valley; Seattle, hosting Microsoft, Amazon and others; Austin, which has come to be known as a center for semiconductor work; the longstanding technology cluster in Boston. When we shift to measures of absolute specialization, we find a considerably different list. San Francisco, Washington DC, Seattle and Boston remain, but certain large metropolitan areas emerge as highly-ranked centers of employment in information technology: New York, Los Angeles, Chicago, and Philadelphia. The case of Los Angeles is instructive. Southern California hosts a large agglomeration of information technology, centered on Orange County. It is one of the nation's largest in absolute terms. Yet Los Angeles appears nowhere in the higher echelons of relative specialization (it ranks 31st among all metropolitan areas on this basis), and its location quotient is low. Although it is the fourth largest agglomeration in the U.S. – making it larger than those of celebrated clusters in Boston and Seattle – the hub of information technology concentrated in the Los Angeles region is rarely mentioned in discussions of U.S. high technology centers. The public debate, implicitly centered on relative, not absolute specialization, throws big shadows over this complex reality.

Of these two measures, however, the clearest theoretical case exists for specialization defined in absolute terms. Increasing the size of a localized activity agglomeration should raise the productivity effects of spatial concentration through the three main mechanisms specified by theory: sharing of input suppliers; matching of specialized labor demand and labor supply, especially in a context of high-turnover industries; and technological learning or spillovers, especially where innovation involves many different types of actors spread across different organizations (Duranton and Puga, 2004; Rosenthal and Strange, 2004).

By contrast, there is less theoretical clarity and consensus for why having a high share of an activity would improve economic performance. Over the years, three principal notions have been developed that suggest that growing relative specialization will produce economic benefits. The first concerns competition between sectors for resources in the regional economy. Consider a regional economy with a sector that has a high share of regional employment and output. Due to this footprint, the agglomeration will exercise a dominant role in regional demand for labor, land, infrastructure and other resources. If we further assume that regional factor supplies and infrastructure are not perfectly supply elastic, or even that they have strong frictions, then a high level of relative specialization would minimize certain kinds of congestion effects that might appear in a more diversified regional economy. This might result in productivity levels that are positively related to relative specialization.

This is descriptively plausible. Firms in any given industry might prefer not to have competition from other sectors if this minimizes their production costs in a region. But the region might very well prefer to develop other activities, even if they raise competition for factors and resources and ultimately drive out the dominant sector. From the perspective of the region this may be preferable if this diversification of its economic base entails movement up the ladder of technological sophistication and productivity. Standard theory would always prefer the latter outcome and would predict it, using standard assumptions about factor mobility and local economic succession. Empirically, regions fare very differently when faced with this kind of complex problem of local economic adjustment. Some succeed in moving onward and upward, while others enter into a vicious circle of loss of employment and population. The problem is that there seems to be no general model that explains how relative specialization, by minimizing resource competition, would be systematically good or bad for regional economic development. Thus, upon closer examination, it does not provide much justification for the benefits of a narrow regional economic base.

A second variant of the relative specialization hypothesis is an institutional version of the first. Chinitz (1961) once proposed that dominant industries command the political attention of the region in which they are located, and that this complements the way they can quasi-monopsonize factor markets, as in the discussion above. Contrasting New York and Pittsburgh, Chinitz suggested that the outcomes of this could be favorable if the industry is a promising or dynamic one, while it can be negative if it is not. Subsequently, Mancur Olson (1965) developed a more general theory of how interest groups capture attention, leading to "institutional sclerosis," whereby the ability of institutions to reallocate resources to new domains of activity and functioning is diminished. Thus, if we borrow from Chinitz's positive example, it follows that some forms of relative specialization could be helpful to a regional economy via the way they create dynamic industry groups, but if we borrow from his less positive example or more generally from the Olson hypothesis, relative specialization leads to elite capture and sclerosis.

These are obviously interesting and plausible theoretical notions. In political science, they have been tested in a number of policy-making areas, and are a major theme in large-scale institutional theory as applied to long-term processes of national economic development (Persson and Tabellini, 2002; Grossman and Helpman, 2002; Acemoglu et al, 2001;

Acemoglu and Robinson, 2008). To our knowledge, however, there has been no large-scale test of whether high levels of relative specialization lead to these political-economic effects at the regional scale, and in turn whether such effects shape long-term adjustment of regional economies in a positive or negative way.

A third version of the relative specialization hypothesis can be drawn from recent debates in economic geography and what is known as the "new regionalism." These discussions draw on theories of agglomeration. They explore the idea that an agglomeration of producers is simultaneously an interacting supply system; a local labor market matching system; and a context for knowledge exchange and spillover. But it is more than the sum of these parts: it is also a functioning ecosystem, tied together by many kinds of specialized economic agents, such as "dealmakers," supportive local governments and associations, habits and soft conventions, and supportive inputs such as finance, and R&D (Storper 1997; Morgan, 1997; Feldman and Zoller, 2012). It stands to reason that there is just so much room for these ecosystems in any given region, even in very big ones. This third hypothesis about relative specialization would then be that if a region wants to have these highly-performing ecosystems, it cannot accommodate too many of them.

No discussion of relative specialization would be complete without mentioning a long-standing version of it: the idea that a region is relatively specialized when an industry has a higher share in the regional economy than it does in the national economy. This concept, canonized in the location quotient, is an indicator in search of a theory. The strongest theory one can adduce in its support is the notion that there is a fixed external (national or international) demand for the output of a sector, so that if a region is specialized in a sector with external demand that increases faster than the regional demand, then the specialization will be favorable to regional growth. But it can readily be seen that it offers no general predictions about whether a high location quotient will be good or bad for regional income or employment; that depends entirely on whether one specializes in a sector with high external growth or not. Evidently, this could go either way.

Table 3 summarizes our discussion of the various theories regarding the economic development implications of specialization, and evaluates the arguments on the basis of theoretical grounds as well as the evidentiary basis for each.

Table 3: Typology of theories of the development effects of specialization

SPECIALIZATION Type	ARGUMENT	SOLID ARGUMENT?	EVIDENCE
IA. Overall level of specialization / diversification	Spreads risk from external shocks	- Addresses shocks, not opportunities - Urbanization economies do not enhance diversification - Main benefit is from size not diversification per se	No hard evidence that diversification raises long-run regional employment levels or quality
IB. Overall level	Dynamic version: relatedness through diversification helps evolution	Is it diversity or complex "related" specialization?	Evidentiary claims extremely sensitive to definition of "related". No consensus about this.
IIA. Relative (share) specialization	Reduces competition for factors/congestion costs	Not clear why would be good for regional economy as whole	
IIB. Relative (share) specialization)	Focuses political-elite attention	Chinitz hypothesis supported by institutionalist literature	-Difficult to test at any scale -No large-sample tests at regional scale
IIC. Relative (share) specialization	New regionalism	Not just industries, but their supporting environments, ecosystems	Case studies suggest this, but lots of conceptual imprecision. No large-scale tests.
III. Absolute specialization (size of cluster)	Scale leads to greater productivity	-Theory on sharing, matching, learning = at least the first two strongly scale dependent; third should have positive scale effect through specialization and diversity of knowledge community	Some confirming evidence in urban economics

4. Measurement: What Goes Together and Comes Apart?

In order to investigate these concerns empirically, we have to be able to measure specialization. Specialization should include activities that are similar or closely related, and the term diversification should refer to an economy based on activities that are heterogeneous or unrelated. Operationalizing these notions of "similar" or "related" (or their opposites) is not easy. Theory instructs us to look for functional inter-relatedness in terms of input-output relationships among localized firms. Measures of relatedness should capture not only the links among buyers and suppliers, but also connections that arise through shared labor pools and common ideas. Moreover, we would also like to capture the ecosystemic aspects of specialization described above: networks, conventions, dealmakers, etc. Unfortunately, these requirements are too onerous to be practical; they constitute ideals against which we should measure the possible.

The standard statistical categories for capturing specialization are supposed to group together activities that have similar outputs, and by virtue of this, would be based on similar production techniques and factor inputs. In the United States, this is the idea behind the Standard Industrial Classification (SIC), and more recently, the North American Industrial Classification System (NAICS). But different levels of similarity will be captured by the scale of aggregation of the NAICS category used to perform the empirics of specialization, ranging from the highly-aggregated one-digit level that distinguishes manufacturing from wholesale activities and so on, to far more detailed six-digit industries.

This choice of aggregation or "granularity" is vitally important. The typical consulting report and many academic articles employ two- or three-digit NAICS codes. These aggregate together disparate activities that are unlikely to be functionally related or similar to one another. For instance, three-digit NAICS codes group together graphic design, tax preparation and the design of computer systems. It is not plausible that these activities regularly constitute part of a coherent specialization. Two- and three-digit industry codes therefore create groups that contain high levels of internal heterogeneity. Homogeneous commodity industries, or those that have a simple and unified technological base (and hence production function) across a variety of outputs, are very rare. Studies of specialization using highly aggregate classifications will generate rankings that are highly questionable.

If high levels of aggregation lump together activities that are substantially different in their effects on employment and income, then statements about them reflect invidious comparisons. This point can be seen in Table 4, where we compare wages associated with specialization in the aggregate category of information technology in Los Angeles and San Francisco. Both regions have large absolute concentrations of high technology, as noted above, but the San Francisco Bay Area has a much higher level of relative specialization. However, the wages that workers earn in information technology activities in Southern California are considerably lower than in Northern California. On average, information technology workers in Los Angeles earn a bit less than 70 percent of their colleagues in the Bay Area. One sensible interpretation is that, in fact, we are comparing apples and oranges: the San Francisco area is likely specialized in different subsectors (products or functions) of high tech than its southern neighbor.

Table 4: Average Wages in Information Technology Sectors 2010

Sectors	Average Wages: Los Angeles	Average Wages: San Francisco
Overall IT Agglomeration		
Information Technology Agglomeration (43 6-digit sectors)	\$86,169	\$128,216
Selected Individual 6-digit Sectors		
Software publishers (511210)	\$128,583	\$169,432
Custom Computer Programming Services(541511)	89,295	111,648
Computer System Design Services (541512)	90,874	111,312
Computer Equipment and Software Merchant Wholesalers (423430)	80,416	155,961

Note: Authors' calculations based on data from County Business Patterns. Wages are averages expressed in nominal 2010 dollars. For a full list of the sectors that are part of the IT agglomeration, see Appendix A.

Even when we disaggregate, the differences persist. The lower part of Table 3 compares wages across Los Angeles and San Francisco within individual, six-digit information technology sectors - the most detailed industrial data commonly available. To ensure we are not examining small outliers, we confine our results to sectors in which both regions are highly specialized. For instance, San Francisco software workers earn around 30 percent more than workers in the same narrow sector in Los Angeles. Wage differences could reflect differences in productivity within a subsector, but it seems more likely that SF is producing different outputs, using different techniques and factor inputs, from LA. Aggregation masks this heterogeneity, which has been amply confirmed in studies on international trade and technological upgrading. Researchers have found considerable international variation in sophistication even using 10-digit product-level data (Schott, 2005; Kemeny, 2011). Further disaggregation is therefore not a practical solution to this problem because there is so much unobserved heterogeneity in the economy. But this ought to raise flags about any statement about specialization, and confirms our suspicion that most of the academic and policy literature about specialization is comparing apples and oranges. To make things more complex still, dangers are not limited to insufficient detail – there may also be such a thing as too much disaggregation. To take an example, it seems sensible to jointly consider changes in specialization in such six-digit NAICS sectors as "Custom Computer Programming Services (541511) and "Computer Systems Design" (541512). Yet, if we address the issue of internal heterogeneity by defining industries using the greatest industrial detail, we arrive at another problem: we have now considered that each six-digit sector ought to exist within an entirely isolated silo, with no relationships to other six-digit industries.

It seems then, that an improved approach would seek to combine detailed sectoral data into larger groupings reflecting substantive interconnections. We followed this course when compared IT in California regions in Table 3, curating a list of relevant six-digit sectors from various classes. For instance, our list included "Semiconductor and Related Device Manufacturing," (334413) and "Computer System Design Services" (541512), despite the fact that, on the basis of their location in the classification system, these ought to be unrelated or highly dissimilar industries. But these sectors are actually closely related, and this is reflected in their high level of geographical co-location.

This ad hoc approach does not solve the problem of internal heterogeneity, but it helps us combine detailed industry data into something that better resembles our understanding of specialization, in information technology at least. Ultimately, we need an algorithmic method of performing these tasks for the entire economy. Economic geographers and urban economists have sought an approach to address this problem of 'industrial distance' (Ellison and Glaeser, 1997; Frenken et al, 2007; Boschma and Iammarino, 2009). Though a research agenda is solidifying around this problem, as yet there is no widely agreed upon method for distinguishing related from unrelated segments of the economy. This is an urgent problem whose solution could potentially improve our understanding of specialization.

Given the present state of affairs, however, statements about specialization – descriptive or statistical – should be interpreted with great prudence and "league table" or rankings of hot spots should be taken with more than a grain of salt.

5. Specialization and Development: A Test of Specialization Effects on Incomes

Having discussed the theoretical case for specialization, and explored the difficulties of its measurement, we now investigate the relationship between economic development and specialization empirically. For this exercise, we focus on one aspect of the broader discussion above: exploring the links between productivity and relative and absolute specialization. Specialization, whether relative or absolute, may certainly affect other dimensions of development, such as population or employment growth, but we are most interested in its relationship to the 'quality' of growth. Like much of the literature, we measure productivity using data on wages. Wages are the best available gauge of worker productivity (Feldstein, 2008). And in the context of cities, evidence suggests that rising worker productivity is expressed in higher wage levels (Combes at al, 2005). Wage data, as compared with output data from the Census of Manufactures, is also less likely to introduce bias due to mis-measurement (Ciccone and Hall, 1996).

A standard approach in the agglomeration literature links productivity to the relative or absolute size of a sector (and sometimes a city). This approach predicts the wages of individual workers, as follows,

$$w_{ijk} = \alpha + \beta_1 S_{jk} + \beta_2 X_i' + \beta_3 C_k' + \varepsilon_i \qquad (1)$$

where *w* represents wages for individual *i* in industry *j* and city *k*; *S* indicates some index of industry specialization or agglomeration; *X'* describes a vector of individual characteristics, such as educational attainment, experience, gender etc., *C'* is a vector of city-specific characteristics; and ε is an error term satisfying classical regression properties. Estimates of Equation 1 commonly use ordinary least squares (OLS) on large cross-sectional data like public-use samples of the Decennial Census of Population and Housing (for some prominent examples, see Wheaton and Lewis, 2002 and Glaeser and Maré, 2001). This method offers some advantages, not least that such data cover large numbers of individuals.

However, this approach suffers from at least two major issues. The largest and most widely discussed problem is that of bias due to unobserved heterogeneity. While the available large, individual-level datasets commonly include a variety of wage covariates, they do not cover the full breadth of worker differences. Bias from this source could be very large; for instance, Yankow (2006) finds that two-thirds of the city-size wage premium is due to unobserved worker differences. Variation in wages could be due to specialization or they could instead reflect unobserved differences in worker ability or effort.

A second issue arises from the dearth of data on individuals over time that could be used in order to track the co-movement of specialization and wages. At its heart, any theory about the links between specialization and economic outcomes is about how changes in specialization patterns might produce changed economic circumstances. Unfortunately, such rich linked time-series data do not exist for the U.S. (nor for most other countries).[4] Cross-sectional worker data simply do not allow us to shed light on dynamics.

One sensible compromise would be to use data offering repeated measures on industries in regional economies. Following this more feasible approach, we adopt the following model,

$$\overline{w}_{jkt} = \beta_1 \overline{w}_{jkt-1} + \beta_2 AS_{jkt} + \beta_3 RS_{jkt} + \beta_4 N'_{jk} + \beta_5 C'_k + \mu_{jk} + \eta_t + \upsilon_{jt} \quad (2)$$

where $\overline{w}$ is the average wage for workers in industry *j* in city *k* at time *t*; *AS* measures the level of absolute specialization for an agglomeration(*industry x city)*; *RS* is the level of relative specialization for a given *industry x city*; *N'* is a vector of time-varying *industry x city* characteristics; *C'* is a vector of dynamic city-level characteristics; μ represents an individual *industry x city* fixed effect; η represents a year fixed effect, and ν is the standard error term. Equation 2 also adds a one-period lag of the average wages in an agglomeration, since

[4] The Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) is the closest data of this kind for the U.S., though it offers very scant establishment information. Access to such data are also somewhat out of reach: access is restricted to approved researchers, with approval often taking very lengthy periods.

workers' wage levels are not set anew each year, but are instead anchored by the wages earned in the previous period. Just as an individual's wage is not annually renegotiated from a blank slate, average *industry x city* wages in the current year should be related to average wage levels from the prior year.[5]

Equation 2 explores how productivity levels in an agglomeration respond to changes in its relative and absolute levels of specialization. Taking a concrete example, our approach seeks to identify how the wages of workers in New York City's financial services sector are influenced by changes in this agglomeration's absolute size and relative footprint in the region. The *industry x city* fixed effect absorbs all stationary heterogeneity across agglomerations. That is, it addresses the problem of comparing apples and oranges that plague cross-sectional explorations, whether those apples and oranges are individual workers or local agglomerations. Meanwhile, the year dummy variable accounts for unobserved time-specific shocks that exert uniform impacts across all *industry x city* units, such as business cycles. Equation 2 therefore offers a number of advantages over estimates of the impact of specialization on wages produced using the more common specification shown in Equation 1. First, Equation 2 accounts for a wide array of sources of spurious correlation, not least the problem of comparing apples and oranges. It also exploits temporal dimensions of the data. Moreover, by confining the studied relationship to within-sector effects, we avoid having to consider an almost-unlimited number of other possible causes of inter-sectoral wage spillover effects. For these reasons, it ought to provide an improved gauge of the association between specialization and productivity.

[5] Including lagged dependent variables as predictors can be a tricky procedure, with the possibility that such variables will (incorrectly) swamp the effects of other predictors of interest. We discuss this and methods of correcting for such problems further in the results section, but this problem does not afflict the results of this empirical inquiry.

5.1 Data

To estimate Equation 2, we use the U.S. Census Bureau's *County Business Patterns* dataset. *County Business Patterns* provides annual information about industries in individual counties. The data offer a number of key advantages. First, they are comprehensive: they provide details of every industry in each county in the U.S. Second, because they are an annual series, they can be assembled and analyzed as a panel dataset. Third, they offer detailed industrial granularity, with industries defined at the 6-digit North American Industrial Classification System (NAICS) level after 1997. Fourth, they are released in a relatively timely manner, such that our analytical data run from the incorporation of the NAICS system in 1998, all the way up to 2010.

The data are not, however, without their own issues. They describe a small range of characteristics of regional agglomerations, chiefly payroll, employment and information about the number and size distribution of firms.[6]Moreover, their high degree of geographic and industrial detail means that it is difficult to supplement the minimal data with other information from external sources, since these supplementary data can scarcely match their granularity. Such a small range of variables would be highly problematic in cross-sectional studies. However, using fixed effects, any stationary differences among industrial clusters are irrelevant to the analysis. This approach may not suit all research questions, but it is apt for an investigation into the responsiveness of productivity to changes in specialization.

The 'regions' to be studied are Metropolitan Areas, as defined by the Office of Management and Budget (OMB). OMB defines metropolitan areas to reflect functional social and economic integration as determined by commuting ties. *County Business Patterns* includes information on 292 metropolitan areas. The dependent variable in the forgoing analysis is the average annual wage income for workers in each *industry x city* agglomeration,

[6] There are also some issues with employment data that is suppressed due to reasons of confidentiality (Issserman and Westervelt, 2006), though this may not be true in more recent samples.

derived by dividing total annual payroll in an agglomeration by the number of its employees. We measure absolute specialization as the number of employees in a local agglomeration. We calculate relative specialization as the share of employment in a local agglomeration in total metropolitan employment. As controls, we include total metropolitan employment. This indicates the breadth of overall agglomeration economies, which may be related to wages and productivity. Prior research also suggests that its absence may bias estimates using measures of relative specialization (Combes, 2000). Because of evidence indicating that industry productivity is partly a function of the distribution of the sizes of its constituent firms (Acs et al, 1999, Pagano and Schivardi, 2003), we also include an indicator of average industry firm size.

We define local agglomerations using four-digit NAICS sectors. Equation 2 seeks to examine how changes in the size of a localized industry affect the wages it pays. As noted earlier, if the boundaries of an industry are defined too narrowly, then we will ignore changes in specialization in related sectors. Conversely, if industry definitions are too broad, then changes in employment will include many activities that will have little effect on the wages of our 'true' sector's workers. There is therefore a need to strike a balance in terms of the level of industrial granularity. We opt for 4-digit industries because they seem to offer this balance, though we conduct sensitivity analysis at different levels to ensure our findings are not purely the result of our chosen level of industrial detail.

Rather than estimating the impact of changes in specialization in the full range of industrial sectors that compose the broader economy, we discriminate among industry types. Agglomeration studies have focused mainly on manufacturing, and in some cases on services. We focus on tradable sectors for the reasons discussed in previous sections.

Following Jensen and Kletzer (2006), we identify tradables by looking at patterns of geographical concentration. It is assumed that tradable industries are concentrated in relatively few locations in the U.S., while spatially ubiquitous sectors are non-tradables. Using County Business Patterns data for 2010, the following Herfindahl index of geographical concentration is constructed for each four-digit sector:[7]

$$Conc_j = \sum_{k=1}^{K} \left(\frac{e_{jk}}{E_j} \right)^2 \tag{3}$$

where e measures employment in industry j and city k; and E is total employment across all cities in industry j. Industries with Herfindahl values near zero will be those that exhibit a uniform distribution over space, while Herfindahl values closer to one indicate sectors where activity is highly concentrated in only a few locations.

As with Jensen and Kletzer, we must choose a cutoff point in the distribution of concentration values at which tradable activities are distinguished from non-tradables. There is no clear theoretical guidance on such a cutoff. By closely examining the data, we settle on a cutoff point of around 0.036. Industries with Herfindahl values below 0.036 conform to our expectations regarding industries that ought to be non-tradable: retail stores of various kinds, death care services, car repair, warehousing, architectural services, machine shops and other general purpose machinery manufacturing. Meanwhile, industries with index values above 0.036 seem likely to be tradable. These include motor vehicle parts manufacturing, software publishing, electric lighting equipment manufacturing, and pipeline transportation of crude oil. While the precise location of this cutoff is not derived from theory, in empirical terms it sensibly differentiates non-tradable from tradable sectors.

[7] Though Jensen and Kletzer use locational Gini coefficients, the Herfindahl index made more sense to us, because it is explicitly about concentration – another way to say specialization. See Wolfson (1997) for a comparison of the two measures. We explored the sensitivity of results to the choice of alternate years, including 2000 and 2005. Results did not materially vary.

5.2 Results

Initial results reported in Table 5 are estimated using pooled ordinary least squares. We start from this naïve approach for exposition purposes. The final model uses a different estimation technique and represents our best estimate of the relationships of interest. Year fixed effects are included in all models in order to account for economy-wide time-specific shocks.[89]

Model 1 estimates a simplified version of Equation 2 in which relative specialization is the sole specialization measure; Model 2 does the same using only absolute specialization. Relative and absolute specialization are related by construction, though they are only moderately correlated (corr=0.34, p=0.000). This is because overall employment levels, which form the denominator of the relative specialization measure, are influenced by a host of factors unrelated to the dynamics of individual industrial clusters. Diagnostics performed on OLS estimates, such as the variance inflation factor (VIF) test, indicate no problems of multi-collinearity among these or other variables. Nonetheless, our initial two models focus on each specialization measure separately. In pooled cross-sectional models, both measures are positively and significantly related to average wages when they alone indicate specialization. We can interpret Model 1 as indicating that industries that occupy larger shares of their regional economy also pay higher wages, while Model 2 suggests that large industries in cities tend to pay higher wages. In Model 3 we include both aspects of specialization at once. Though magnitudes of the coefficients for each specialization measure decline somewhat, both remain positively and significantly related to average *industry x city* wages. Hence a naïve interpretation of these results would say that New

[8] In initial exploration, city and industry dummy variables were also included. These would account for the effect of any stationary city-wide or industry-wide shocks. Since these did not materially change the results for the variables of interest, we do not report these here. These dummies also got unwieldy in the more complex approaches that follow.

[9] While it is common for researchers to log transform some variables, especially wages, we opt against this approach, choosing to leave variables in their natural scale. We do so mainly because of the size of our dataset. While non-normality of predictors can indicate potential problems of non-normality of the residuals, this issue is not likely to bias estimates produced using a dataset with so many observations. In most cases, logging did not materially affect results.

York's finance workers earn more than their counterparts in Los Angeles both because Wall Street employs more workers, and because it agglomeration occupies a larger share of overall employment in New York than the same industry does in Los Angeles.

However, these preliminary results ignore four important econometric considerations. First, as we discuss above, for the purposes of identification, it makes sense to utilize repeated observations on *industry x city* units. The OLS models pool together all *industry x city x time* observations, but do not recognize the temporal relationships within *industry x city* units. By exploiting the time dimension, we can incorporate dynamics while permitting fixed effects estimation that shifts the examined relationship to one occurring within groups. Taking a fixed effects approach, we can model how wages in a particular local agglomeration change in response to changes in specialization over time in that unit.

Second, given the likelihood that average wages depend on past realizations, it is desirable to include a lagged iteration of average wages on the right side of the equation. In the context of the OLS models (1) – (3), we opted not to do so given well-documented issues of bias in that context (Achen, 2000; Keele and Kelly, 2006). Even in a panel setup, dynamic pane bias is a widely discussed problem. The standard solution is to apply some form of the Generalized Method of Moments (GMM) estimator (Bond, 2002; Arellano and Honore, 2001). In addition to being apt in the presence of an autoregressive dependent variable, this class of model is also suitable for large-N, small-T panels such as the one at hand. For this reason, rather than applying the standard fixed effects estimator to equation (2), we estimate the model using two-step GMM-FE.

Table 5. Estimates of dynamic relationship between specialization and wages, 1998-2010

Dependent Variable: Average Industry x Region Annual Wage				
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	GMM-FE IV
VARIABLES				BW(2)
Relative Specialization	3,839***		1,953***	-265.5
	(109.8)		(126.5)	(649.6)
Absolute Specialization		0.597***	0.486***	0.279***
		(0.009)	(0.010)	(0.081)
Lagged Average Wages				0.233***
				(0.033)
Metro employment(thousands)	2.025***	1.272***	1.425***	4.48***
	(0.028)	(0.031)	(0.032)	(0.783)
Average Firm Size			0.683	-28.48***
			(0.797)	(4.968)
Constant	27,499***	28,248***	27,764***	
	(151.2)	(203.7)	(150.8)	
Observations	114,155	114,155	114,155	72,923
Groups				17,160
Year Dummies	Yes	Yes	Yes	Yes
R-squared				0.17
First-stage *F*-statistic				91.14
Hanson *J* Statistic				1.044
(Chi-square p-value)				(0.307)

Note: Asterisks indicate significance levels:*** p<0.01, ** p<0.05, * p<0.1. Models 1-3 estimated with heteroscedasticity-robust standard errors. Model 4 estimated using two-step robust GMM with HAC standard errors produced with a 2 year bandwidth.

Endogeneity, and specifically bias from reverse causation represents a third potential estimation issue. While theory predicts a causal relationship running from specialization to productivity, it is sensible that rising wages and productivity could stimulate changes in specialization. Employment in sectors with rising wages may grow in absolute and relative terms as workers shift from other locations, as well as from other industries in the same city. Both indicators of specialization are potentially endogenous in this regard. Lacking ready access to randomized control trials, we attempt to account for endogeneity using instrumental variables techniques. As always, the problem of finding suitable instruments looms large. GMM techniques are useful in this respect, as they provide methods of incorporating lagged regressors as instruments. We avail ourselves of this strategy, but also add an additional 'substantive' instrument for absolute specialization, adapting a shift-share approach that Card (2001) applies in the context of the economic effects of immigration. We calculate the 'predicted' size of employment in a region's industry in time t on the basis of its size in period *t-1* and the overall national industry growth rate between *t-1* and *t*. Industry-specific national historical employment growth rates are given by:

$$g_{jt-(t-1)} = \left[\left(e_j / E \right)_t - \left(e_j / E \right)_{t-1} \right] \Big/ \left(e_j / E \right)_{t-1} \tag{4}$$

where $g_j$is the growth rate in employment *e* for industry *j*in the national economy with a total employment of *E* between *t* and *t-1*. Given these growth rates, the shift-share 'predicted absolute specialization' index $\overline{\overline{AS}}$ is constructed as follows:

$$\overline{\overline{AS}} = e_{jkt-1} \left[1 + \left(g_j \right)_{t-(t-1)} \right] \tag{4}$$

Since current wages can determine neither prior levels of employment in a local agglomeration, nor historical national industry employment growth, this index is a potentially useful exogenous source of variation. Its appropriateness as an instrument will be discussed below.

Serial autocorrelation represents a fourth and final estimation problem, one which could bias standard errors. We detect the presence of serial autocorrelation in the panel data using a test created by Wooldridge (2002).[10] We apply the standard Newey-West approach that uses the Bartlett kernel to produce heteroscedasticity- and autocorrelation-consistent (HAC) estimates. In initial work, we explored bandwidths from 2 to 5 and found consistent results in each case.For brevity, we present findings estimated with a bandwidth of 2.

Model 4 addresses these four econometric concerns; it is fixed effects model with lagged as well as substantive instruments for potentially endogenous regressors, estimated using two-step GMM with HAC covariance estimation with a bandwidth of 2. Together,

[10] We conduct Wooldridge's test using the Stata command 'xtserial'.

these methodological choices ought to produce efficient estimates of the coefficients and standard errors, while strengthening confidence on the direction of causality in the observed relationship, while also accounting for dynamic panel bias and serial autocorrelation. We estimate the model on over 20,000 local *industry x city* agglomerations. Due to the shift in estimation strategy from OLS to FE, the magnitudes of coefficients in Model 4 are substantially different from those obtained in Models 1–3.

Model 4 more conclusively demonstrates that absolute specialization is positively and significantly related to wages. The coefficient on this variable suggests that, as employment in a local agglomeration grows by 100 workers, average annual wages in that cluster will rise by around $29. This seems fairly modest, but it is worth considering that this effect is larger than the overall urban agglomeration effect: with a coefficient of 4.32, a similar increase in urban population will augment wages by only $0.43. Interestingly, after accounting for the temporal dimension of the data, relative specialization is negatively related to wages, though insignificant. In fact, over a very wide variety of fixed-effects estimates, ranging from those with no instruments and lagged dependent variables to fuller models with all of the characteristics accounted for in Model 4, absolute specialization is uniformly positive and significant, while relative specialization is uniformly negative (and mostly insignificant). This holds not only for four-digit industrial data, but also for panels constructed using two-, three-, five- and six-digit data. The striking differences between cross-sectional and panel results points to the need to carefully revisit the findings of prior studies that do not explore temporal dynamics.

The lower panel of Table 5 displays diagnostics of the instrumental variables. Specifically, the first-stage F statistic is far above the threshold value of 13.43, suggesting that we can conclude that our instrument set is not weak. The Hansen J value indicates that at least one of our instruments can plausibly be treated as endogenous. These results increase the confidence with which we can consider that the direction of the observed relationship goes from specialization to wages and not the other way around.

6. Conclusion: Specialization and the Dynamics of Economic Development

In keeping with theories of agglomeration central to the field of economic geography, we find that growing absolute specialization is linked to rising wages, while changes in relative concentration are not significantly associated with wage dynamics. These theories hold that scale augments productivity chiefly through sharing, matching and learning. However, the insignificant relationship between relative specialization and wages stands in contrast to results obtained using cross-sectional, between-industry approaches, probably because our method eliminated a lot of the noise (unobserved heterogeneity) in those approaches.

Our empirical exercise leaves unexplored many other potential dimensions of the relationship between specialization and regional economic development. One such dimension is the link between incomes and the type, rather than the level, of specialization. New Yorkers might be richer on a per capita basis than Angelenos because NY has high relative and absolute specialization in finance and business services, which are very high wage sectors. We have only confirmed that as finance grows bigger in absolute terms, New Yorkers working in that sector will see their wages rise. Research at the international scale confirms that countries with tradable sectors positioned near the top of the global ladder of product sophistication and quality do indeed have higher incomes than those chiefly oriented toward activities occupying the lower rungs (Kemeny, 2011; Hausmann et al, 2007). Applied to metropolitan regions, this reasoning suggests that specialization is related to development not so much through a general effect of overall levels of specialization, whether absolute or relative, as through the 'what' of specialization. The region's position in the economy-wide division of labor matters most to regional wages and per capita incomes, through its effect on terms of trade and production technique, which act upon factor composition and prices.

Of course, in smaller regional economies, it follows that devoting greater effort to a more sophisticated activity will enhance the favorable effect of that specialization on the regional economy. This will mechanically raise levels of absolute and relative specialization in the favorable sector, and unleash the productivity effect that we detect above. The combined effects of 'doing the right thing' and doing so at a larger absolute scale, will move wages and incomes in the same positive direction. Inversely, an economy positioned far down on quality and innovation ladders is unlikely to resolve its income level problem by simply by increasing the scale – relative or absolute – of its agglomeration.

The most significant dimension of specialization, then, is the classical meaning of the term, i.e. concerning not the scale but the 'what.' This issue is dealt with in development theory through the notion of comparative advantage; in economic geography it features in theories that account for the locational sorting of tradable activities between regions, on the basis of the combination of trade costs and agglomeration economies, as well as the evolution of sectors within places.

In the background of any consideration of the dynamics of specialization in an open global economy is the issue of the complex relationship between forces for regional convergence and divergence. Why do some city-regions fall down the income rankings (Cleveland, Detroit), while others climb up (Houston, Dallas), and still others manage to maintain their positions at the top while transitioning their tradable sectors (San Francisco, Boston), and still others climb up a bit and then stagnate in the middle of the ladder (Las Vegas, Phoenix)? This evidently, though not entirely, has to do with the shifting industrial makeup of these places. In that process, change in specialization is not an entirely exogenous cause – it is partly an outcome – but it plays an important role.

Along these lines, some of the relative specialization hypotheses we discussed in section 3, but which we did not test in this paper, make claims about possible favorable effects of good relative specialization at t leading to good (or better) specialization at $t+n$. Notice that these hypotheses are not about maintaining or growing the same favorable specialization over time, but about a process of succession by which specializations dynamically affect one another over time and space. There is little in the empirical literature that tests this rigorously.[11] The treatment of this very important issue remains largely qualitative and anecdotal. It reframes the specialization debate as one about development, but we are far from having the theory or measurement techniques adequate to this task. This debate raises the bar for evolutionary theories of the benefits of relatedness and for institutional theories of adjustment.

Practitioners' and policymakers' concern with specializing in the right thing lies behind the popular rankings of regional economies on the basis of their focus on finance, information technology, biotechnology, green technology, corporate headquarters and so on. These actors are rightly concerned with identifying successful places by virtue of the 'what' of specialization. But we have shown that, in many cases, their rankings are based on dubious measures; more careful approaches are needed. This observation applies to more syncretic academic concepts of specialization as well, of which we cite two very popular ones in recent years: "global cities" and "creative cities" (Sassen, 2001; Florida, 2002). These concepts are at base making claims that regional economic performance is meaningfully a function of having a regional economic base that is specialized in activities that are, respectively, 'global' or 'creative'; each has spawned cottage industries in which cities are

[11] Hidalgo et al (2007) is a notable exception.

evaluated and ranked along these lines. Both are about specialization, but both suffer from many definitional problems. The concepts of globalness or creativity (the independent variables) mix sectors, labor force characteristics, and sometimes regional environmental features (such as "tolerance"). Moreover, neither has a clear dependent variable, opting for composite notions of "economic performance" (Florida, 2002) or globalness (Sassen, 2001). The most global cities – New York, London and Tokyo, and many of the rest of the top ten – are not the metropolitan areas with the highest per capita incomes. These wealthiest cities are actually mostly B-level globalization centers such as San Francisco, Oslo, Zurich, and Vancouver. The most "creative" metro areas are generally very high income regions, but we cannot tell whether this is because of their specialization in certain activities, their concentration of certain types of labor, or their environmental characteristics, nor how these different factors interact in any putative causal sequence (Storper and Scott, 2009). One could obtain almost identical results to the "creative city" ranking by throwing out the labor force and environmental variables, and just ranking on the basis of specialization and wages in the tradable sectors; one could equally reverse it and obtain the ratings by using just the occupational composition (reflecting specialization, of course). In other words, neither of these analyses seem to add anything that is not done more crisply by simply analyzing the specialization of these region's tradable economies.

Finally, we can return to the practical issues of using rankings in economic development practice and policymaking. As long as practitioners continue to believe that by shaping regional specialization patterns, they can improve economic development, then rankings such as location quotients or other common measures will continue to exist, no matter that they remain fairly far away from more academic notions of specialization and its dynamics.

But even on their own terms, such ranking practices could be vastly improved. Rankings and classifications somehow need to artfully mix concepts of relative and absolute specialization when they consider a particular set of industries or industry (eg finance, high tech, or 'high wage' or 'high skill' industries), or perhaps include both. A second lesson is that such rankings are basically uninformative if they are not disaggregated to at least the 4-digit NAICS level. There will be little or no relation to income effects at higher levels of aggregation. Of course, even that does not fully solve the issues of industrial relatedness or similarity that we discuss above.

A third and final lesson has to do with the relationship between specialization and quantitative growth prospects of regional economies. As noted, the principal practical tool for attempting to estimate these effects is through relative specialization measures such as location quotients. These measures suffer from their lack of a dynamic model of the locational structure of the industry in question. A rise in external demand will not automatically benefit a regional economy if the industry's locational structure is changing and the industry is highly contestable across locations. A good contemporary example of this is the logistics industry in Southern California. The region has a high level of absolute and relative specialization in this sector, and a high national location quotient. But this cannot be used to predict anything about quantitative employment changes in the region if the sector's overall economic geography is shifting (new Panama Canal) or if capital is rapidly being substituted for labor (e.g. bigger ships, containers and trucks). Shift-share analysis can only capture this retrospectively, and – cruelly – even when it captures a favorable shift-in-share, it cannot simultaneously include the absolute size of the industry at national scale, nor the industry's national employment density and quality.

This brings us back, once again, to the multidimensional nature of measuring specialization and the need to artfully mix the several facets of specialization – absolute, relative, share, and quality – to have any value to applied regional analysis. Both the academics and economic development professionals are in general far from such a high standard. This paper is an attempt to move us one step forward, but many unanswered questions remain in order to gain a full understanding of the effects of levels and types of specialization on regional economic development.

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