FIRM STRATEGIES IN SCIENTIFIC LABOR MARKETS

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FIRM STRATEGIES IN SCIENTIFIC LABOR MARKETS

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High tech provides the excitement and the headlines.

–Peter Drucker, *Innovation and Entrepreneurship*

To infinite cities.

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SUMMARY

This dissertation expands on the economic geography literature on how and why innovation clusters spatially by taking a closer look at two correlated phenomena: regional specialization and firm clustering. While existing studies note that innovative regions are often highly specialized and highly clustered, further research is needed on the relative contributions of specialization and clustering to regional innovation. I examine these contributions by focusing on one key element of any regional innovation project: the labor market for scientific and technical professionals.

The foundation for this study is a typology of regions based on regional specialization and firm clustering. I use this typology to answer one key research question: how specialization and clustering affect wages and recruitment methods in science-based industries.

I create my typology using firm location data from the *Photonics Buyers' Guide*, a leading trade publication in the photonics industry; I use the standardized location quotient and the average nearest neighbor distance as metrics of regional specialization and firm clustering, respectively. I investigate small firms' labor market strategies using job search and wage data from the 2012 SPIE salary survey of employees in the photonics industry. I also examine how people-based and place-based policies for strengthening scientific and technical labor markets change when viewed through the lens of specialization and clustering.

I selected the photonics industry as an example of a science-based industry for three reasons: its diversity of applications, its policy importance, and its unique colocation of design and manufacturing.

Regional specialization and firm clustering, while correlated, do not always go hand in hand. By disentangling the effects of specialization versus clustering, this dissertation contributes to the literature on the spatial analysis of innovation. It also offers policymakers a heuristic for deciding on the importance of being known for a particular industry (regional specialization) and creating dense innovation districts (firm clusters) through preferential zoning or other mechanisms.

CHAPTER 1: INTRODUCTION

Agglomeration economies fascinate economic geographers and pop culture enthusiasts alike. From an economic geography perspective, agglomeration economies illustrate the tension between the benefits and costs of concentrating economic activity in a small physical area. When firms and their suppliers colocate in one region, they trade goods, people, and ideas more efficiently. But this colocation also elevates housing prices and crowds transportation systems. In pop culture, Silicon Valley is a case in point. While goods, people, and ideas circulate more quickly within the Valley, the spatial density of economic activity has added pressure to a limited housing supply and an inadequate transportation infrastructure. And yet engineers keep flocking to Silicon Valley in a twenty-first century gold rush, lured by the promise of six-figure technology jobs.

Economic geographers and industry analysts have not yet explained how agglomeration economies influence wages and recruitment methods. While there is some evidence of a wage premium in agglomeration economies, the mechanism of this premium remains unknown. Perhaps the larger number of qualified job seekers, combined with the larger number of firms hiring, leads to increased competition for talent that bids up wages. Perhaps the physical proximity of firms encourages workers to discuss market rates for salaries with competitors more regularly. Or perhaps an entirely different mechanism is responsible for the wage premium in agglomeration economies.

Similarly, while there is some evidence of the importance of strong labor market intermediaries (LMIs) in agglomeration economies (Benner 2002; Christopherson and Clark 2007; Saxenian 2002), the degree to which such LMI roles are limited to agglomeration economies remains uncertain. Perhaps the larger numbers of workers and firms creates an environment too complex to navigate without LMI assistance. Perhaps LMIs function similarly in other regional economies, even without industry-specific agglomerations. Or perhaps it is a mixture of these two narratives.

In this dissertation, I focus on agglomeration economies in science and technology (S&T) industries. Both federal and regional policymakers prioritize S&T investment. At the federal level, investments in S&T industries span the technology lifecycle from early-stage research in universities to Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) grants for small businesses to commercialize new inventions to multi-million dollar defense technology contracts. At the regional level, investments in S&T industries are inextricably intertwined with narratives of reinvention. Whether through explicit attempts to recreate Silicon Valley or through support for biotech, nanotech, and other technology clusters, regions compete with one another for the firms, workers, and prestige American culture attaches to advances in science and technology.

In the S&T policy of the post-World War II boom, manufacturing was a central focus for its ability to absorb scientific advances and its stability as an employer. Then, over the next several decades, factories shut down and relocated overseas, seeking lower costs. Journalists and social scientists alike spoke of the decline of manufacturing, and wondered what could take its place. The rise of service jobs—for both the "creative class" of white-collar professionals (Florida 2002) and the "contingent labor" (Peck and Theodore 2001) of the new blue-collar world—raised questions about the relationship between advances in S&T and labor markets. In the old model—or what Stone (2004) would call production regime—advances in S&T were translated into better practices on the factory floor, and thus directly linked to blue collar labor. In the old model, career ladders were clear, pensions were guaranteed, and unions provided access to collective bargaining. In the new model, career ladders span more organizations (Arthur and Rousseau 1996), pensions are uncertain or nonexistent (Clark, Strauss and Knox-Hayes 2012), and collective bargaining is rare (for a few counterexamples, see Frommer (2003) on film, and Van Jarrsveld (2004) and Brophy (2006) on tech workers in Seattle).

And then, at the height of the offshoring narrative, manufacturing began to reemerge in the United States in three ways: (1) through "onshoring"—firms returning to the United States from abroad; (2) through maker movements, small scale craft production detailed in Clark (2014); and (3) through advances in industries like photonics, which colocate design and manufacturing because doing it any other way is simply too expensive. In this dissertation, I use the photonics industry as a case study. Photonics is the science and technology of light. End products derived from photonics research include fiber optic cables, magnetic resonance imaging (MRI) machines, lasers, and more. Because photonics influences such a wide variety of industries, from telecommunications to medicine to defense, it is what researchers call a platform technology. Policymakers often target platform technologies for investment as a mechanism to transform many industries. For example, in the United States, the Integrated Photonics Institute for Manufacturing Innovation (IP-IMI)—announced in November 2014—is a $110 million federal investment in photonics, managed by the Department of Defense.

This dissertation addresses economic geographers' gap in understanding how agglomeration economies influence wages and recruitment methods by disentangling two related aspects of agglomeration economies: clustering and specialization. Clustering refers to the physical proximity of firms from a single industry in a metropolitan area. Specialization refers to the degree to which a single industry is under- or over-represented in a metropolitan area compared to the nation. The central research question of this dissertation is this:

> RQ: How do specialization and clustering affect wages and recruitment methods in science-based industries?

Distinguishing between specialization and clustering in this way allows me to test whether the wage premium scholars find in agglomeration economies results from the relatively higher number of firms and workers (specialization), the close physical proximity of those firms and workers (clustering), or something else entirely. Similarly, this distinction allows me to test whether the relative prevalence of various recruitment methods in agglomeration economies results from specialization, clustering, or another factor. In doing so, this dissertation provides the foundation for future work on how different aspects of agglomeration economies affect labor market processes including, but not limited to, wage setting and recruiting.

My research question assumes that specialization and clustering are empirically distinct phenomena. In this dissertation, I show that while specialization and clustering are correlated ($r = -0.78$, $p < .001$), there exist regions that are high in one dimension and low in the other. For example, the Los Angeles-Long Beach-Santa Ana, CA metropolitan area is low in specialization and high in clustering for photonics, and the Worcester, MA metropolitan area is high in specialization and low in clustering for photonics. This analysis is based on a dataset I constructed of over 3,000 firms in the photonics industry. I obtained the firm data from the *Photonics Buyers' Guide* (PBG), a leading trade publication in the industry that includes records for firm names, founding years, addresses, and websites. I created regional profiles of specialization and clustering by geocoding the firm data, assigning each firm to its 2010 Census metropolitan area using a point in polygon analysis, and calculating standardized location quotients (specialization) and average nearest neighbor distances (clustering) for each metropolitan area.

Given that specialization and clustering are indeed empirically distinct, I moved forward with my research question: How do specialization and clustering affect wages and recruitment methods in science-based industries? I answered this question through a series of OLS regressions. The first set predicted the log of an employee's annual salary from specialization, clustering, and a set of controls known to be associated with wages (gender, education, years of experience, and employer size). The second set predicted how an employee found a job from the same set of independent variables: specialization, clustering, and controls. I found that clustering, not specialization, is responsible for the wage premium we find in agglomeration economies. Moreover, I found that neither clustering nor specialization have an effect on recruitment methods in agglomeration economies.

The source of employee data for my OLS regressions is a survey of over 3,000 employees in photonics: the 2012 SPIE Salary Survey. SPIE is one of the largest photonics industry associations in the world; its name is not an acronym. Jennifer Clark and I helped design the survey. Krisinda Plenkovich, SPIE's policy director, provided us with the anonymized responses. I measured wages and recruitment methods through two survey questions:

> [1] What was your total 2011 annual pre-tax earnings at your current job, including all salary and bonuses?
>
> [2] How did you find your current or original position at your present employer? (Select one)
>
> - Printed job advertisement (newspaper or journal)
> - Online job advertisement
> - In-person job fair
> - University career office
> - Alumni network
> - Professional association
> - I was recruited
> - Private placement agency
> - Public/government placement agency
> - Networking or referral through personal contact
> - I contacted the employer directly (no job was advertised)

- Other ____________________________

I coded the second question according to Granovetter's (1995) three categories of finding a job: networking, directly contacting an employer when no position is advertised, and labor market intermediaries such as job boards and recruiters. I geocoded each employee response and assigned each response to its 2010 Census metropolitan area using a point in polygon analysis. I then appended the specialization and clustering statistics for the employee's metropolitan area to each employee record using a join based on the metropolitan area ID. The resulting dataset contained variables for employee wages, recruitment methods, demographic controls, clustering, and specialization.

Given that clustering, rather than specialization, accounts for the wage premium in agglomeration economies, policymakers may benefit from reassessing the place-based versus people-based policies debate. Place-based policies—from enterprise zones to neighborhood-specific payroll tax incentives for technology firms—can be thought of as a means of encouraging clustering. People-based policies—from vocational skills training programs to broad-based tax credits for specific industries—can be thought of as a means of encouraging specialization. Place-based policies are not always better than people-based policies. Rather, place-based and people-based policies offer complementary approaches. They both have their place in a policy portfolio.

The remainder of the dissertation is structured as follows. Chapter 2 reviews the relevant literature, highlights the gaps in our knowledge, and illustrates how my research question addresses one of these gaps. Chapter 3 explains my selection of methods. Chapter 4 presents my results. Chapter 5 concludes with a discussion of the research results in the context of relevant literature, policy recommendations based on the research, and directions for future work.

CHAPTER 2: LITERATURE REVIEW

The central research question of this dissertation is this:

> RQ: How do specialization and clustering affect wages and recruitment methods in science-based industries?

I approach this question through the lens of relational economic geography. In short, it is known that economic activity is unevenly distributed across social and spatial structures, and that social structures both shape and are shaped by economic structures. While much is known about how networks and labor market segmentation affect labor market outcomes, little is known about how agglomeration affects these outcomes. I add to the growing literature on the relationship between agglomeration and labor market outcomes by distinguishing between two related aspects of agglomeration—specialization and clustering—in order to test their effects on wages and recruitment methods.

Relational economic geography: the social and spatial embeddedness of economic activity

Economic phenomena both shape and are shaped by the social contexts they inhabit. In other words, "the economic and the social are fundamentally intertwined" (Bathelt and Glückler 2003, 118). Social structures facilitate economic exchange; contracts between firms and the trading of stocks would be unthinkable without some degree of social trust. Such activities would also be unthinkable without formal institutional structures and laws (Baum and Oliver 1992). The fact that economic phenomena are made possible by social and institutional structures is encapsulated in the concept of economic embeddedness (Granovetter 1985). Markets are not only economic networks, but also social networks (Knox-Hayes 2009). Further, the social and institutional structures that support economic activity are themselves spatial (Massey 1984). Labor markets are spatially bounded and a product of the interactions among employees, employers, and intermediaries (Peck 1996). Firms are spatially bounded in that they inevitably operate in a particular place or set of places; each place has its own social norms, institutions, political dynamics, and local, state, and national policies (Maskell 2001).

In an example from the policy realm, Christopherson and Clark (2007c) argue that firm strategies and policy environments are mutually constitutive. Firms lobby for particular policies—they influence the policy environment—but at the same time, existing policies constrain the options available to any given firm. Further, firms influence regions through the hiring and firing of employees, contracting relationships with suppliers (Storper and Walker 1989), and interactions with customers and policymakers (Grabher 1993).

One key task in economic geography is conceptualizing how firms survive. In brief, the theory of the firm in economic geography posits that firms have a set of core competencies from which they derive competitive advantage. The question of how firms create these competencies is a primary site of analysis and theorization: “Economic geographers have made a central contribution in their turn through their work on the effects of proximity, distance, and local context—on, let us call them, the softer sources of innovation" (Amin and Thrift 2000, 7).

Economic geography approaches the effects of proximity, distance, and context on innovation by emphasizing the relationships among actors involved in firm innovation. Bathelt and Glückler (2003, 123) argue that regions are not spatial concepts independent of economic phenomena; instead, they argue for a "relational economic geography" in which "economic action transforms the localized material and institutional conditions of future economic action." They describe the aims of relational economic geography as follows:

> Research in relational economic geography thus focuses on processes, such as institutional learning, creative interaction, economic innovation, and interorganizational communication, and investigates these through a geographical lens, rather than uncovering spatial regularities and structures. Economic processes and relations broadly defined are at the heart of this approach which integrates (and requires) both economic and social theory. (Bathelt and Glückler 2003, 125)

Relational economic geography relies on a critical realist epistemology. This is a middle-road epistemological position: It aims to develop general, causal explanations but recognizes that the many filters of human perception mean that although an objective reality exists, two individuals are unlikely to have the same subjective experience of observation (Sayer 2000). Critical realism is thus neither logical positivist nor postmodern (Bathelt and Glückler 2003, 127). This dissertation adopts the critical realist perspective.

How networks shape labor market outcomes

Individual social and professional networks play a large role in the workplace. These networks affect recruitment processes and formal contracts at the interviewing and job offer stages; they affect the psychological contract once an employment relationship between firm and worker begins; and they affect retention when an employee is choosing whether to stay in her current position or seek out a new one.

In terms of recruitment processes and formal contracts, networking is a common path to finding a job (Granovetter 1995), particularly among technical contractors in Silicon Valley (Barley and Kunda 2006). In the United States, applicants to jobs who have been referred by a contact within the organization earn more interviews and job offers than non-referred applicants do, even when controlling for resume quality and application timing (Fernandez and Weinberg 1997). Preliminary work suggests that hiring managers in large firms in China also prefer recruiting through employee referrals, as they believe referred applicants are of higher quality (Han and Han 2009). However, the effects of networking differ based on industry and gender. Referred applicants seem to have no greater chances than non-referred applicants to entry-level factory jobs (Fernandez and Fernandez-Mateo 2006), and overall, networking seems more beneficial for men than for women in professional and managerial applications (Forret and Dougherty 2004).

Given research on perceptions of job candidates, this finding makes sense. Hiring managers construct images of the "ideal" employee—images that often include demographic attributes such as age, race, sex, and country of origin in addition to the ability to do the job (McDowell, Batnitzky and Dyer 2007). These images in turn drive decisions about how much to spend on recruitment, where to recruit, and how to evaluate candidates. Further, these recruitment decisions differ by job role, with far greater resources devoted to high wage labor that is seen as less substitutable than low wage labor (Carnoy, Castells and Benner 1997).

In social network terms, a strong tie exists between two individuals when they frequently contact one another or feel emotionally close to one another. Family members and close friends are examples of strong tie relationships. A weak tie exists between two individuals when they have met one another, but do not meet frequently or do not feel emotionally close to one another. Acquaintances and distant professional contacts are examples of weak tie relationships. In general, an individual's strong ties have access to the same information the individual does, while an individual's weak ties are more likely to have access to information that the individual does not already know. This is why weak ties are often a better source of information on new job opportunities (Granovetter 1973).

In any given social network, a structural hole exists where two individuals are nonredundant in terms of both cohesion and structural equivalence (Burt 1995). Cohesion refers to tie strength: two individuals connected by a strong tie are redundant, while two individuals connected by a weak tie or by no tie at all are nonredundant. Structural equivalence refers to the degree to which two individuals share mutual contacts: two individuals with fifty mutual friends between them are redundant compared to two individuals with only two mutual friends between them. For example, in the network of Google employees, a structural hole exists between two engineers if they have never met and if they do not have any mutual contacts. When employees broker structural holes (connect two people who are otherwise unconnected) and form strong friendship ties within the firm, they consider firms to have more performance-related (balanced) and short-term, monetizable (transactional) obligations to them (Ho, Rousseau and Levesque 2006).

Individual networks also influence employee retention. Networking is a valuable means of acquiring information on the state of the labor market, and this information can be used in deciding whether to pursue a new position. One empirical model, drawn from a synthesis of qualitative and quantitative studies, indicates that employees network to gain information when they know that their potential contacts have valuable information and when they can access those contacts quickly and cheaply (Borgatti and Cross 2003). In particular, networking is correlated with turnover; employees who build wide social and professional networks are more aware of external opportunities and thus more likely to change employers (Wolff and Moser 2010).

Both individual and firm networks matter for labor market outcomes. Firms intentionally create networks with other firms for a variety of reasons: to share risks, access new markets, get products to existing markets faster, share skills, protect their property rights, and access knowledge not immediately available through other means (Pittaway, Robertson, Munir, Denyer and Neely 2004, 145). In general, networking is associated with product, process, and organizational innovation (Pittaway, Robertson, Munir, Denyer and Neely

2004). In particular, both direct ties (in which firms are directly connected to one another through a contracting relationship or other collaboration) and indirect ties (in which firms are connected to each other through an intermediary or another firm) positively influence innovation (Ahuja 2000).

Further, relationships among firms are heavily influenced by spatial proximity (Breschi and Malerba 2001). The closer two firms are geographically, they more likely they are to collaborate or share information—in other words, to transact with one another as legal entities (Takeda, Kajikawa, Sakata and Matsushima 2008). This is one of the major supposed benefits of industry clusters (Porter 2000): the ability of firms to take advantage of the scale effects of having many firms with overlapping expertise in one place. However, recent empirical work has shown that the benefits of spatial proximity are largely confined to a very small distance. Even in the advertising industry in densely populated Manhattan, two firms are much more likely to collaborate if they are located less than 750 meters from each other (Arzaghi and Henderson 2008). That said, both geographical location and network positioning matter for firm innovation; studies suggest that locating in an industry cluster and a occupying a central network position among managerial ties both lead to higher levels of innovation (Bell 2005).

Firms' relationships with other firms outside the region are also important. Strong relationships with non-regional customers and suppliers provide ideas that facilitate firm innovation (Doloreux 2004). Informal networks among small manufacturing firms are often non-local, as the best source of information to solve a business problem may be located elsewhere (Kingsley and Malecki

2004). Regional and non-regional sources of knowledge are important inputs to innovation (Doloreux 2004), even though innovation itself is quite geographically concentrated (Audretsch and Feldman 1996).

Even within an industry cluster, relationships among firms are unequal. Large, multinational corporations play a disproportionately powerful role in firm networks (Christopherson and Clark 2007; Yang and Hsia 2007). Large firms influence the supply chains of small firms and anchor clusters (Yang and Hsia 2007). Compared to small firms, large firms (including multinational corporations) also have greater access to resources such as capital, skilled labor, research and development facilities, and intellectual property—key inputs to the innovation process (Christopherson and Clark 2007). It is thus no wonder that large firms attempt to influence regional innovation policies in their favor (Christopherson and Clark 2007). Regional policymakers do have choices (Bristow 2010; Christopherson and Clark 2007): they can influence how much it costs for firms to operate within the region, which types of research regional universities should conduct, which types of skilled workers universities should produce, and which types of lifestyle amenities the region's cities should provide to lure firms and skilled workers to the region. These choices have a profound influence on the shape of regional innovation and on the character of firms in a regional labor market.

How labor market segmentation shapes labor market outcomes

Related work on the effect of labor market structures on labor market outcomes rests upon the foundation of segmented labor market theory. This line of work emerged due to a set of empirical, theoretical, and policy issues with neoclassical labor market models (Cain 1976). The critical issue is the persistence of unemployment juxtaposed with the persistence of open positions. In other words, even when the number of jobs available is equal to the number of people looking for work, not everyone finds a job. When supply equals demand, the market does not clear. Segmented labor market theorists addressed this issue by positing the existence of a dual labor market consisting of a primary (high-wage) segment and a secondary (low-wage) segment. Empirically oriented economists then tested dual labor market models alongside single labor market models on wage and employment data. In short, dual labor market models better explained the distribution of wages and employment compared to single labor market models (Dickens and Lang 1988).

After the initial wave of econometric work, economic geographers began to explore labor market segmentation by gender, class, ethnicity, space, and place as well as by wages (Bauder 2001; Massey 1984; Peck 1996). One key segment is contingent workers. Although definitions differ, part-time workers and contractors are often considered contingent (Peck and Theodore 2001) or precarious (Kalleberg 2009) workers. Contingent work is characterized by a fundamental insecurity about future employment (McDowell and Christopherson 2009). In low-wage labor markets, day laborers and other kinds of short-term contractors are a case in point (Padavic 2005). In high-wage labor markets, contingent workers are often software engineers or other professionals who work as freelancers on a contract basis (Kunda, Barley and Evans 2002). While contingent work has alternately been heralded as an empowering development for entrepreneurial, free agent workers and a sign that the social safety net of a steady paycheck with benefits is crumbling, the reality is more complex (Barley and Kunda 2006). Some contingent workers do find empowerment and joy in being able to set their own schedules and avoid unpleasant colleagues, while others have trouble supporting their families with their unpredictable incomes.

Another way to segment labor markets is by industry. A key finding in economic geography is that labor markets in different industries work in dramatically different ways. For example, the labor markets of semiconductor engineers in the United States in the 1980s were characterized by high turnover during booms and low turnover during busts; these workers could afford a high rate of inter-firm mobility because their expertise was industry-specific rather than firm-specific (Angel 1989). More recently, on Wall Street, the emphasis on shareholder value—in other words, maximizing short-term rather than long-term profitability—leads finance firms to engage in mass hiring and mass layoffs in response to immediate market conditions (Ho 2009). That said, some investment banks outside the United States still have internal labor markets for entry-level and mid-level hires (Royal and Althauser 2003).

No matter the segmentation, all labor markets consist of at least three sets of actors: employers, employees, and intermediaries. Labor market intermediaries include temporary employment agencies, university career services offices, workforce development offices, professional associations and trade societies, and third-party job boards like Monster.com and Dice.com, as well as career-oriented social networking websites like LinkedIn.com. Labor market intermediaries help innovative regions develop because they serve three key functions: they reduce transactions costs, build networks, and manage risk (Benner 2003). For example, ethnic professional associations like The Indus Entrepreneurs (TIE) in Silicon Valley help new high-skilled immigrants find jobs and other professional opportunities by providing a network of people that understand both the host country business culture and the home country business culture. These professional associations also help coordinate joint ventures between home and host country (Saxenian 2002).

How agglomeration shapes labor market outcomes

The *Oxford Dictionary of Human Geography* defines agglomeration as follows:

> The process and outcome of concentrating in one location a set of interlinked and interdependent economic activities. The word 'agglomeration' functions as both a verb and a noun. Large and/or dense agglomerations are sometimes known as 'growth clusters'. Studies by economic and development geographers have practical implications because governments, among others, are keenly interested in having successful agglomerations in their territories. These not only enjoy sustained growth but are also in locations that, for whatever reason, are deemed to be strategically important. See also agglomeration economies, clusters. (Castree, Kitchin and Rogers 2013, 7)

For example, many film studios, casting shops, screenwriters, entertainment lawyers, and more run their businesses in Hollywood. They are all interdependent. And, most importantly for this dissertation, they are all located close to one another. For example, aspiring filmmakers would do well to move to Los Angeles. In the United States alone, finance in New York, music in Nashville, and electronics in Silicon Valley are examples of agglomeration economies.

Agglomeration reduces transport costs for goods, people, and ideas

Marshall (1920) hypothesized that agglomeration benefits firms by reducing transport costs for goods, people, and ideas. Why? First, when firms locate closer to their suppliers, they procure goods more quickly and cheaply. Similarly, when firms locate closer to their customers, they spend less time and money on shipping. Further, when many firms from a single industry locate close to one another, suppliers have an incentive to go where are the firms are. For example, Los Angeles is a very lucrative place for an entertainment law firm to set up shop.

Second, when firms locate close to one another, the firms collectively increase their access to a large pool of skilled labor. If enough of the most skilled workers in the film industry locate near Los Angeles, then LA-based film studios get access to all the top talent in the world—not only by virtue of their social networks, but also thanks to doing business in an agglomeration economy.

Third, when firms locate close to their suppliers, their customers, and each other, they create something like a petri dish for ideas. All of the individuals involved in the agglomeration meet each other formally, through interfirm transactions and collaborations, and informally, through meetup groups, social networks, and happenstance encounters at bars and restaurants. Such face-to-face meetings are a primary mechanism for exchanging ideas. Thus when one firm adopts a process or product innovation, it will not be long before other firms incorporate the new ideas and methods into their processes or products. Legal barriers like patents and non-disclosure agreements notwithstanding, the fastest way for a firm to learn to do new things is to poach a bunch of employees from a place where those new things were done.

Face-to-face contact helps circulate ideas. But that is not all. Agglomeration economies simply do not work without significant “buzz”—people meeting up and networking. Storper and Venables (2004) argue that face-to-face contact serves four key functions in agglomeration economies. First, face-to-face contact is an excellent communication technology when people need rapid feedback—and when they exchange information that is not codified easily, such as the experience of working with a particular person. Second, face-to-face contact helps build trust in relationships, so a hiring manager trusts that a candidate referred by *her* trusted colleagues will do well. Third, face-to-face contact accelerates people’s socialization into professional group norms, so new entrants to an industry get up to speed quickly. Fourth, face-to-face contact taps into the universal human desire to seek pleasure, in part through gaining access to high status. In the workplace, this means employees want to feel the rush of pride and pleasure that comes from being recognized for a job well done.

Agglomeration economies benefit firms by reducing the transport costs of goods, people, and ideas. And face-to-face contact provides the social glue for all this to happen. In 1920, Marshall did not have the data to test his hypotheses. Recent work supports Marshall’s ideas: agglomeration accelerates the exchange of goods, people, and ideas among establishments described in the US Census of Manufacturing (Ellison, Glaeser and Kerr 2010).

But agglomeration has mixed effects on firm performance

Despite these benefits, economic geographers have found mixed results when testing the effects of agglomeration on firm survival and performance. For example, in a study of knitwear firms in Germany, Staber (2001) found that agglomerations based on a single industry hurt new firms' chances of survival, but agglomerations of related industries helped. For example, a cluster composed entirely of spinning firms would likely hurt member firms, while a cluster composed of a mix of spinning, weaving, knitting, embroidering, clothing, finishing, and design firms would likely help member firms. In contrast, among IT firms in Canada, agglomeration did not influence firm survival at the regional level at all, but it *did* assist in firm survival in a few specific neighborhoods in Toronto (Globerman, Shapiro and Vining 2005). In a study of biotechnology firms across the United States, Folta, Cooper, and Baik (2006) found that agglomeration increased firm performance up until about 65 firms. After that, diseconomies of agglomeration took hold: increased competition drove up wages, housing prices, and utility costs.

It is possible that these mixed results are a consequence of different industry and country samples. After all, knitwear firms and biotech firms do not have much in common. The economic and regulatory environments firms face in Germany, Canada, and the United States differ as well. And we have not taken into account firm size, even though agglomeration may affect small firms differently than large firms.

On this last point, Wennberg and Lindqvist (2010) argue that at least for new firms, the inconsistent results of previous studies are simply due to differences in measures of agglomeration. They find that an absolute measure of agglomeration (the raw number of employees in a given industry in a given region) predicts firm survival and performance better than a relative measure of agglomeration (the location quotient for the target industry in the target region). So it seems that agglomeration, measured in absolute terms, benefits firms—certainly in reducing costs, and potentially in helping new firms survive and all firms perform better.

Agglomeration economies: the policy perspective

Policymakers care about agglomeration. The empirical observation of the spatial concentration of innovative activity (Audretsch and Feldman 1996) provides the foundation for this fascination. The overwhelming popularity in business and policy circles of Michael Porter's cluster approach to economic development (Porter 2000) adds fuel to the fire. A number of regions have attempted to encourage the colocation of firms in special business districts with the hope that such geographical concentration would lead to higher levels of innovation (Lundequist and Power 2002; Martin and Sunley 2003). The popularity of academic and trade non-fiction books on the secrets of Silicon Valley speaks to this point (Saxenian 1996; Kenney 2000; Lécuyer 2005; Turner 2006; Hwang and Horowitt 2012; Menuez 2014). Alternatively described as a war for talent, a competition among regions, and a proliferation of high-tech hubs, regional policymakers throughout the United States, Canada, and Europe have tried to encourage agglomeration in their jurisdictions.

The problem is that spatial concentration is neither a necessary nor a sufficient condition for innovation. Sometimes the geographical concentration of firms leads to captive suppliers and cost-based competition (Florida and Kenney 1990). Similarly, because networking among regional firms is helpful for innovation (Bell 2005), policymakers can try to encourage firms not yet participating in networking to do so (Gellynck and Vermeire 2009).

Studies of regional institutions emphasize the economic development roles of universities, private firms, and government agencies, as well as the "triple helix" created by the interactions between them. The emphasis on interactions between universities, local industry, and local government agencies dates to Frederick Terman's stint as dean of engineering at Stanford in the 1940s and 1950s. Among other things, Terman encouraged collaborations between Stanford and local firms and pushed the university to create the Stanford Industrial Park in 1951 (Leslie and Kargon 1996). However, Terman's model is not easily replicable across regions. During the 1960s, Terman consulted for regions in New Jersey, Texas, and South Korea on the Silicon Valley model. Of these, only the South Korean project was successful (Leslie and Kargon 1996). Similarly, both the University of Pennsylvania and the Georgia Institute of Technology had trouble applying Silicon Valley's lessons during the Cold War (O'Mara 2004). More broadly, institutions and policy discussions should be studied within their historical contexts to understand how, when, why, and where they work (Flint and Shelley 1996; Shelley 2002; Solecki and Shelley 1996).

Since then, economic geographers have tried to understand which parts of the system of universities, private firms, and public policy are key to agglomeration economies and which are just incidental. One key finding is that a strong research university does not automatically lead to regional economic development as measured by patents and spinoff companies (Feldman and Desrochers 2003). Rather, the mission and institutional orientation of the university are more important. Does the university emphasize commerce, science, or both?

In terms of private firms, three key findings emerge. The first is that large firms can often innovate more than small firms because they have disproportionate access to key regional resources like labor and university research capacity (Christopherson and Clark 2007; Christopherson and Clark 2007; Christopherson and Clark 2007). The second is that global production networks, public policies, community politics, and labor market intermediaries all provide boundaries for firms' employment strategy options as well as workers' labor strategy options (Coe and Jordhus-Lier 2010). And the third is that private firms play a key role in the construction of production regimes, which encompass "the technology of production, employment relationships, managerial strategy, worker responses, union organizational possibilities, legal regulation, and social ideology" (Stone 2004).

So how do policymakers benefit from agglomeration? At the regional level, agglomeration is associated with more job creation, higher tax revenues for government agencies, and higher wages for employees (Wennberg and Lindqvist 2010). And it is not just that cities with agglomeration economies create more jobs. The labor markets are *qualitatively* better, too. Employees and firms find better matches in terms of quality (Andersson, Burgess and Lane 2007; Melo and Graham 2014), in the sense of ensuring a good fit between employee and firm. Further, the network structures that allow workers and firms to find each other are consistent across agglomerations, even when comparing very different institutional structures in the UK and Germany (Casper and Murray 2005).

The biggest factor in spatial wage disparities across cities is the distribution of workers' skill levels between labor markets (Combes, Duranton and Gobillon 2008; Yankow 2006). Highly skilled workers get better at their jobs with each move from firm to firm, and the accumulation of skills from decades of job-hopping results in an agglomeration wage premium (Freedman 2008). The exposure to different challenges in different firms often results in job-hoppers gaining skills more quickly than employees who stay with a single firm.

The economic development policy advantages of agglomeration are the higher rates of job creation and the higher quality of those jobs, measured both in terms of wages and fit between employee and employer. Policymakers who want to reap these benefits—more and better jobs—need to find policy mechanisms to encourage agglomeration in the first place. But studying mature agglomerations cannot provide insight into how and why those agglomerations came to be (Feldman and Francis 2004, 132). Despite decades of work on the history and path dependence of key agglomerations (e.g., Sturgeon (2000)), the literature still lacks a definitive explanation of how and why agglomerations come to be. In the absence of any empirical consensus on what makes agglomerations form, what do policymakers do? Martin and Sunley (2003, 23-24) offer a typology of policy attempts to encourage agglomeration:

1. Serve an intermediary function—set up in-person groups and communication mechanisms to bring firms, employees, and research institutions together.
2. Market the region as the best place for a given industry.
3. Provide financial, marketing, and design services for firms in the target industry for agglomeration.
4. Identify weaknesses in the current value chain for the target industry in the region, and then recruit investors and firms to remedy them.

In addition to these functions, regional policymakers can simply pay firms in a target industry to relocate to the region. For example, a chamber of commerce might try to recruit biotech firms to its region, or a state may attempt to lure a new manufacturing plant into its borders. With the right policy coalition across regional and state levels, firms may benefit from economic development plans to waive taxes or receive lump sum payments for relocation.

But do these policy tools actually strengthen scientific and technical labor markets? Some scholars argue that policy attempts to encourage agglomeration do not work (Schmitz and Nadvi 1999), while others argue that top-down policy-driven creation of an industry agglomeration is possible in certain places and at certain times (see Depner and Bathelt (2005) on an automobile cluster in Shanghai). To get to the bottom of what works and does not work with agglomeration and economic development policy, we need to distinguish between two phenomena: specialization and clustering.

Why specialization, and clustering matter for scientific labor markets

Though the notion of agglomeration economies is at least 200 years old—Marshall's *Principles of Economics* was first published in 1890—scholarship in this area has grown exponentially in the last twenty years. Web of Science has records of scholarly works on agglomeration in the field of geography dating back to 1964, and 94% of the 1,038 works were published between 1994 and 2014.

In 1994, AnnaLee Saxenian published her groundbreaking ethnography of Silicon Valley and Route 128: two key agglomeration economies in the United States. Both regions had deep pools of technical talent, strong research universities, venture capital, specialized suppliers, and excellent infrastructure—yet Silicon Valley outperformed Route 128 across a host of economic indicators throughout the 1980s. Saxenian explained Silicon Valley's performance as a product of the region's flexible, network-based, learning oriented business culture. In other words, Silicon Valley's social and firm boundaries were porous, and helpful information flowed across those boundaries quickly, which helped individuals and firms adapt to changing technological and business conditions in the moment.

Saxenian's book generated waves of policy interest throughout the United States and Japan (Saxenian (1996): prologue to the paperback edition). Policymakers asked repeatedly how they could create the kind of Silicon Valley culture that would lead to regional prosperity in their jurisdictions. Saxenian recommended that regional policymakers pursue three different policy strategies (1996):

1. Aid in "stimulating and coordinating cooperation among firms and between firms and the public sector" (166).
2. Support "institutions that provide capital, research, managerial and technical education, training, assistance to entrepreneurs, and market information" (167).
3. Help "promote collaboration among fragmented and often jealous city and local governments" to address physical infrastructure challenges from transportation to housing to environmental concerns (168).

Four years after Saxenian's paperback edition, Michael Porter argued that economic developers should focus their efforts on the regional scale—and particularly on upgrading clusters. In his widely cited article, Porter defines clusters as

> geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions (e.g., universities, standards agencies, trade associations) in a particular field that compete but also cooperate. (Porter 2000, 15)

In other words, Porter's clusters can be seen as agglomerations. More importantly, they are agglomerations of *related industries*. Porter suggested that clusters help firms uncover new market needs and identify new ways of addressing existing needs. These innovations form the foundation for both firm and regional advantage—both of which are regional policy priorities. Porter offered several strategies for policymakers to encourage clusters (2000, 28):

1. Serve as a facilitator in bringing different firms and government agencies together.
2. Invest in education, training, and research programs to support the interrelated industries in this particular cluster; also provide financial assistance via recruiting foreign investment, establishing special economic zones, and the like.
3. Remove barriers to competition by streamlining relevant regulations.

Saxenian and Porter agreed on the first two strategies. For the third, Saxenian emphasized bringing together disparate localities to upgrade physical infrastructure, while Porter focused on deregulation. During this debate, policymakers around the world latched onto the term "cluster" and its promises of regional advantage. Academic scholarship tried to keep pace. Figure 1 shows the growth in literature in geography alone indexed under the topic header "clusters." Clustering literature grew much faster than scholarly work on agglomeration and specialization.

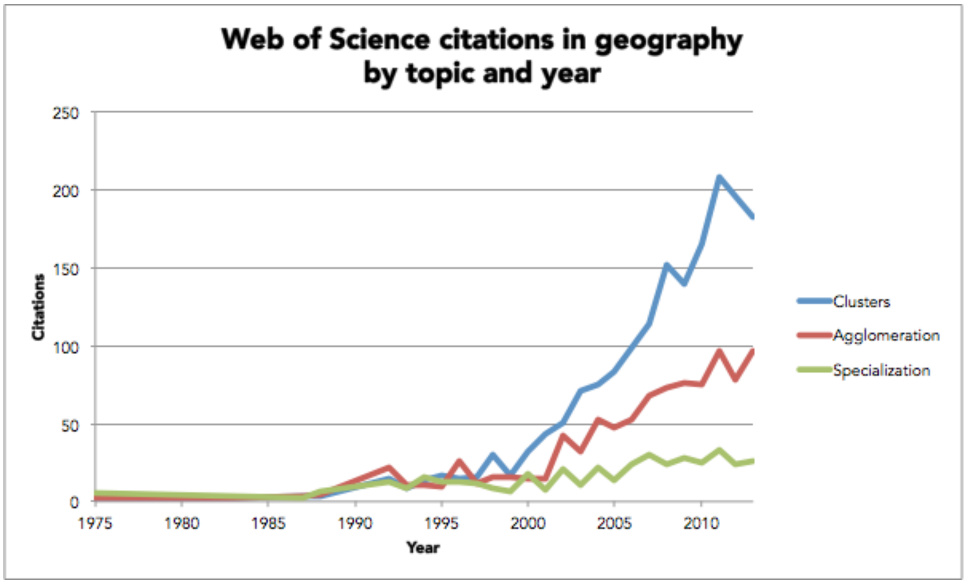


Figure 1. Web of Science citations in geography by topic and year.

The term "cluster" grew so fast in academic and policy circles that by 2003, Martin and Sunley asked if the idea of clustering was a "chaotic concept or policy panacea." Judging by the 573 (and counting) articles that have cited Martin and Sunley's article, their argument hit a nerve. The heart of Martin and Sunley's critique is definitional confusion: what counts as a cluster? They presented different authors' definitions, as shown in Figure 2 (Martin and Sunley 2003, 12).

12 • *Martin and Sunley*

Table 1. Clusters: the confusion of definitions

Porter (1998a, p. 199) 'A cluster is a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities.'
Crouch and Farrell (2001, p. 163) 'The more general concept of "cluster" suggests something looser: a tendency for firms in similar types of business to locate close together, though without having a particularly important presence in an area.'
Rosenfeld (1997, p. 4) 'A cluster is very simply used to represent concentrations of firms that are able to produce synergy because of their geographical proximity and interdependence, even though their scale of employment may not be pronounced or prominent.'
Feser (1998, p. 26) 'Economic clusters are not just related and supporting industries and institutions, but rather related and supporting institutions that are more competitive by virtue of their relationships.'
Swann and Prevezer (1996, p. 139) 'Clusters are here defined as groups of firms within one industry based in one geographical area.'
Swann and Prevezer (1998, p. 1) 'A cluster means a large group of firms in related industries at a particular location.'
Simmie and Sennett (1999a, p. 51) 'We define an innovative cluster as a large number of interconnected industrial and/or service companies having a high degree of collaboration, typically through a supply chain, and operating under the same market conditions.'
Roelandt and den Hertag (1999, p. 9) 'Clusters can be characterised as networks of producers of strongly interdependent firms (including specialised suppliers) linked each other in a value-adding production chain.'
Van den Berg et al. (2001, p. 187) 'The popular term cluster is most closely related to this local or regional dimension of networks . . . Most definitions share the notion of clusters as localised networks of specialised organisations, whose production processes are closely linked through the exchange of goods, services and/or knowledge.'
Enright (1996, p. 191) 'A regional cluster is an industrial cluster in which member firms are in close proximity to each other.'

Figure 2. Martin and Sunley's (2003) summary of cluster definitions.

Some definitions emphasized the geographical concentration of a single industry; others focused on related industries. Some definitions emphasized collaborative relationships between firms, while others highlighted connections between non-firm institutions in a geographical area. Some definitions focused on the need for a certain size threshold—only a "large group of firms" counts as a cluster—and others did not include the "scale of employment" as a definitional criterion. At the time, this table represented but a small subset of all cluster definitions. Clustering is a compelling example of a fuzzy concept (Markusen 2003). In the twelve years since Martin and Sunley's article, cluster research and policy initiatives have continued to grow without much improvement in definitional clarity. So where do economic geographers go from here?

I suggest that we use *agglomeration* as an umbrella term—one that captures all of the variations of the cluster concept. In this sense, agglomeration refers to both the process and the result of the colocation of interdependent economic activities. Then, to clarify the effects of agglomeration, I suggest we use a set of narrowly defined and strictly measured sub-concepts for various aspects of agglomeration.

This dissertation emphasizes two aspects of agglomeration: the identification of "strong" industries for regional economies, and the spatial density of firms within "strong" industries. Thus I propose we use the term *specialization* to refer to the degree to which an industry is over-represented in a region compared to a national baseline. We can measure specialization with a standardized location quotient (O'Donoghue and Gleave 2004). I then propose we use the term *clustering* to refer to the spatial concentration of firms within a target industry. We can measure clustering with an average nearest neighbor distance.

I discuss my choice of measures much more in the next chapter. In this chapter, the key point is that distinguishing between specialization and clustering within the context of agglomeration economies helps us cut through the forest of contradictory effects. If we define and measure two aspects of agglomeration economies, we can find out whether those aspects make a meaningful difference to labor market outcomes like wages and recruitment methods.

Summary

Given that social structures both shape and are shaped by economic structures, understanding agglomeration requires understanding both its social and economic dimensions. In terms of social dimensions, the networks that connect individuals and firms are related to two key labor market outcomes: wages and recruitment channels. These network effects are unevenly distributed by race and gender. In terms of economic dimensions, segmented labor market theory shows that even when the number of job openings and the number of job candidates are equal, the market does not clear. Instead, candidate-job matching occurs in smaller labor markets segmented by skill, gender, race, and space. Against this background, policymakers in major metropolitan areas throughout the United States and the world attempt to encourage high-tech agglomeration in their districts. These policy strategies are partly in pursuit of more and better jobs alongside higher tax revenues, and partly in pursuit of the cultural capital that accrues to high-tech hubs like Silicon Valley. In order to understand how high-tech agglomeration affects labor market outcomes—particularly wages and recruitment channels—more work is needed. Perhaps network structures and labor market segmentations function similarly in high-tech agglomeration economies and outside them; perhaps they do not. To address this gap, this dissertation distinguishes between two related aspects of agglomeration—specialization and clustering—

in order to test their effects on wages and recruitment methods. The next chapter explains the dissertation's methods.

CHAPTER 3: METHODS

Most studies of agglomeration use the term "cluster" in some way—and that term is fraught with a multitude of conflicting theoretical and empirical definitions. These conflicts partly explain the inconsistent results of previous work on the effects of agglomeration on scientific and technical labor market quality. In the literature review, I proposed a way out of this conundrum: define and measure specific aspects of agglomeration separately, then test the relationships between each aspect of agglomeration and the outcomes that policymakers prioritize. In this chapter, I explain how this dissertation does exactly that.

Research question and hypotheses

In this dissertation, I focus on two aspects of agglomeration of interest to policymakers: specialization and clustering. *Specialization* is the degree to which an industry is over-represented in a region compared to a national baseline. *Clustering* is the spatial concentration of firms in a target industry within that region. I argue that it is impossible to select appropriate economic development policies without understanding which aspects of agglomeration are most correlated with regional policy goals such as higher wages, more jobs, and higher tax revenues.

As a proof of concept, I narrow my scope to a regional policy goal of higher wages, then test how specialization and clustering relate to that goal. I begin by showing that specialization and clustering are indeed empirically distinct aspects of agglomeration. I then proceed to test the effects specialization and clustering on wages and recruitment patterns in scientific and technical labor markets. My research question for the dissertation is this:

> RQ: How do specialization and clustering affect wages and recruitment methods in science-based industries?

Table 1 provides my hypotheses. My first two hypotheses concern the role of labor market intermediaries—key institutions that link employees looking for work with employers looking to hire. I expected to find variation in the use of labor market intermediaries based on the degrees of specialization and clustering present in a given metropolitan area. My third and fourth hypotheses address wages, one of the key effects of agglomeration. I expected that the wage gains scholars have found in previous literature on agglomeration were due to specialization, not clustering.

Table 1. Hypotheses for the dissertation.

Hypothesis	Testing	Justification
H1 Recruitment and regional specialization	High regional specialization increases the use of labor market intermediaries (LMIs) for recruitment if the number of firms in the region is also high (≥ 50).	Key studies of the electronics labor market in Silicon Valley highlight the role of LMIs like recruitment agencies, temporary labor firms, and professional associations in making the connections between employees and employers (Benner 2002; Saxenian 1996).
H2 Recruitment and firm clustering	High firm clustering decreases the use of LMIs for recruitment if the number of firms in the region is also low.	Close proximity facilitates information exchange (Arzaghi and Henderson 2008); workers in more tightly clustered firms should know more about job opportunities through their local networks and have less of a reliance on intermediaries.
H3 Wages and regional specialization	High regional specialization increases wages.	Competition among firms bids up the price of labor; previous studies find wage premiums in agglomerations.
H4 Wages and firm clustering	High firm clustering has no impact on wages.	The labor market for wage-setting extends beyond the neighborhood of nearest firms; overall MSA trends should have the biggest effect.

Measuring specialization

In this dissertation, I measured specialization using the standardized location quotient (SLQ). The SLQ is a variation of the location quotient, a widely used tool in economic development policy for identifying "strong" or export-oriented industries within a region.

The location quotient as a measure of specialization

Regional policymakers who pursue industry-specific agglomeration as an economic development strategy must choose which industries to target for their jurisdictions. One of the most common tools for making that choice is the location quotient. Widely used and criticized since the 1940s, the location quotient measures the concentration of a particular industry in a metropolitan area compared the concentration of the industry across the country. It is expressed as follows:

$$LQ_i = \frac{e_i/e}{E_i/E}$$

where

- e_i = employment in focal industry *i* in region
- e = total employment in region
- E_i = employment in focal industry *i* in nation
- E = total employment in nation

The location quotient measures what percentage of employees in a region work in a certain industry, then divides that by the percentage of employees in the nation who work in that industry. It offers a way for policymakers to find out whether any industries are overrepresented in their regions. In other words, if software jobs were 5% of all national jobs, but 10% of all San Francisco jobs, San Francisco would have a location quotient of 2.0—it would be specialized in software. Location quotients reveal the geographical hubs for key industries. For example, the Los Angeles metropolitan area has a high LQ for entertainment, the Nashville metropolitan area has a high LQ for music, and the San Jose metropolitan area has a high LQ for electronics. Analysts can also use firm counts rather than employment to calculate location quotients. In those instances, the formula shifts to

$$fLQ_i = \frac{f_i/f}{F_i/F}$$

where

- f_i = firms in focal industry i in region
- f = total firms in region
- F_i = firms in focal industry i in nation
- F = total firms in nation

Either way, the location quotient represents the degree to which the region is more or less specialized in a particular industry when compared to the national baseline for that industry. In this dissertation, I used firms rather than employees for the location quotient for two reasons: (1) this dissertation focuses on firm networks rather than overall employment, and (2) 23% of the firms in the *Photonics Buyers' Guide* do not report employee data.

Table 2 illustrates key ranges of the firm location quotient.

Table 2. Critical values for the firm location quotient.

Value	Meaning	Interpretation
0	Zero firms in the focal industry within the region	No specialization at all
< 1	Proportion of firms in the focal industry within the region is lower than the national baseline	Less specialized than the nation—not a local strength
1	Proportion of firms in the focal industry within the region is the same as the national baseline	Just as specialized as the national average
> 1	Proportion of firms in the focal industry within the region is greater than the national baseline	More specialized than the nation—probably a local strength

While LQs serve as a measure of agglomeration, they cannot explain why agglomeration economies work. Scholars have proposed four mechanisms that accelerate growth in agglomeration economies: (1) firms share suppliers and service providers, which lets them purchase from contractors things they need but cannot afford to provide for themselves in-house; (2) firms spend less time, energy, and money on training because they can poach highly skilled employees from neighboring firms; (3) employees incorporate new product and process innovations in their work more quickly because they are constantly talking to each other about the new stuff on the block; and (4) institutional intermediaries make sure that firms, employees, universities, government actors, and whoever else needs to be involved are talking to each other and sharing information and resources in a productive, timely manner.

While the strength of an industry in a region may be correlated with these mechanisms, location quotients cannot measure these mechanisms directly. But if we take the strength of an industry as just that—the degree to which an industry is overrepresented in a region compared to a national baseline—then we can test its effects on agglomeration outcomes directly. In other words, rather than using a location quotient to find agglomeration economies, I propose that we use a location quotient as a measure of specialization—and then *empirically test* how much specialization correlates to labor market outcomes that policymakers expect to find in agglomerations in science and technology industries.

The standardized location quotient as an improved measure

The key critique of traditional location quotients is that their interpretation is arbitrary. How can an economic developer decide how high of a location quotient is necessary to consider an industry a key regional strength? For example, one urban planning scholar suggests the following interpretation guidelines (Klosterman 1990, 129). If the location quotient is less than 1.0, then the local employment share is less than the national employment share. Analysts interpret this to mean that local production falls short of local demand, so locals import products to make up the difference. If the location quotient is equal to 1.0, then the local employment share is more than the national employment share. In this case, local production meets local demand. If the location quotient is greater than 1.0, then the local employment share is greater than the national employment share. Analysts interpret this to mean that local production exceeds local demand, so locals export products to other regions.

If these guidelines were followed to the letter, an analyst would treat an industry with a location quotient of 0.99 as under-represented while treating an industry with a location quotient of 1.01 as over-represented. Analysts have addressed this difficulty in three ways. First, they have stack ranked industries by location quotient, and only focused on the top few industries within a region—the industries in which the region is most specialized. Second, they have proposed guidelines with 0.75 and 1.25 cutoffs for non-specialized and specialized regions, respectively. And third, they have used other criteria—such as requests from stakeholders to focus on particular industries—rather than the location quotient to select industries to receive economic development funds.

Yet none of these are particularly satisfying alternatives. The location quotient is a useful metric for exploring a region's potential strengths by industry. Analysts just need a more rigorous way to identify the top regional specializations. To provide more rigor, O'Donoghue and Gleave (2004) proposed an improvement called the standardized location quotient (SLQ). The SLQ transforms the location quotient into a new variable with a mean of zero and a standard deviation of 1. Briefly, the SLQ is calculated as follows:

1. Test the distribution of the location quotient for normality.
    a. If normal: proceed to step 2.
    b. If not normal: take the log of the location quotient. Then test the distribution of log(LQ) for normality.

i. If normal: proceed to step 2.

ii. If not normal: use a different measure.

2. Transform the LQ to z-scores as follows:

a. If LQ is normally distributed: $z = \frac{LQ - mean(LQ)}{sd(LQ)}$

b. If LQ is not normally distributed, but log(LQ) is normally distributed: $z = \frac{\log(LQ) - mean((\log(LQ))}{sd(\log(LQ))}$

3. Identify statistically significant LQs using their z-scores. A z-score above 1.96 indicates regional specialization, $p < .05$. A z-score above 1.65 indicates specialization, $p < .10$.

Measuring clustering

In this dissertation, I measured clustering using an average nearest neighbor distance. As indicated earlier, most studies of agglomeration use the term *cluster* in some way. And there are so many such studies—not to mention policy initiatives—that Martin and Sunley (2003) asked how policymakers around the world became captivated by such a chaotic concept. Theoretical and empirical definitions of *clusters* are many and widely varied, without too much overlap between them. But at heart, the cluster concept addresses something many economic geographers have observed over the years: concentrations of smart people in small spaces coincide with innovative activity. Or, as Gertler (2003) put it, there is an "undefinable tacitness of being (there)."

Correlation is not causation. And if even if we could show a causal link between spatial proximity and innovation, we would miss a key part of the story. As Boschma (2005) points out, four other types of proximity also influence innovation. Cognitive proximity helps people communicate with each other—without a shared knowledge base, teaching and learning is impossible. Organizational proximity creates channels through which people may communicate—for example, if two firms enter into a joint venture, their employees now have a reason to meet where they would not have had a reason to do so previously. Social proximity also facilitates communication—people are more likely to share information with trusted friends, friends of friends, and colleagues. Also, institutional proximity—shared laws, rules, cultural norms, and habits—helps people trust and communicate with one another.

Each of these types of proximity offers promising avenues for further research along the lines I model in this dissertation: how do they, independently and together, affect labor market outcomes? Spatial clustering is the best place to start for because it is easy to measure using distances between firms, and it addresses the puzzle of agglomeration.

Different measures of spatial clustering

Economic geographers and city and regional planners have developed a variety of measures for spatial clustering. In this section, I briefly review the measures I considered before selecting the average nearest neighbor distance. My goal was to identify a measure that would allow me to compare the degree of spatial clustering that firms in a single industry exhibit across different metropolitan statistical areas. For example, are photonics firms in Rochester more tightly clustered than photonics firms in Tucson? Are technology start-ups more densely packed in New York or in San Francisco?

Several clustering methods have been used to address such questions. These include the following:

- **Distance from central feature to furthest feature.** The problem with this approach is that 2 miles in Washington, DC is not the same as 2 miles in New York City in terms of population distribution or transportation time or neighborhood boundaries. I ran into the same problem with standard deviational ellipses and standard distances (circles).
- **Cluster and outlier analysis (Anselin Local Moran's I).** It is unclear how to compare the statistic across regions. One potential way is to examine the percentage of firms from the region with positive values for *I* and significant *p*-values.
- **Average nearest neighbor (ANN) index.** The ANN index—not the distance metric—is designed to compare point patterns in one polygon over time. Urban economists and economic geographers use the average nearest neighbor method to compare changes in the spatial distribution of firms over time, or to compare the spatial distribution of firms in one industry to those in another (Ebdon 1985). The significance test does not apply when comparing several polygons at the same time—as in the case of comparing firm clustering scores across MSAs.

- **High/low clustering (Getis-Ord General G).** This metric compares the spatial clustering of particular values (e.g., assessed property values by location, firm revenues by location). It is not suited for the spatial clustering of locations without any associated values (e.g., firm locations without any other firm attributes).
- **Multi-distance spatial cluster analysis (Ripley's K-function).** This metric compares the extent of clustering at multiple spatial scales in one study area. But it is not comparable across study areas.
- **Spatial autocorrelation (Global Moran's I).** This metric is not comparable across study areas.
- **Hot spot analysis (Getis-Ord Gi*).** This metric identifies "hot spots" of unusual activity (e.g., disease outbreaks, firm locations). But cannot compare the extent of clustering across study areas. In this dissertation, I did not focus on finding hot spots of firm neighborhoods; instead, I addressed whether photonics firms in Washington, DC are more clustered than photonics firms in New York City, for example.

After reviewing these metrics on my own, I consulted with five methodologists in spatial analysis. There is no consensus on the best way to measure spatial clustering across study areas: **Darla Munroe** (Associate Professor and Chair of Graduate Studies in the Department of Geography at the Ohio State University)[1] wrote,

[1] http://www.geography.ohio-state.edu/our-department/faculty-more/munroe

> It is not straightforward to test the degree of clustering across multiple locations - most spatial analysis texts do not take deviation from random as sufficient evidence for/against pattern and there is no other absolute metric to provide a null hypothesis. (personal communication, 6/28/2013).

The other four methodologists each offered different approaches.

- **Dajun Dai** (Assistant Professor, Department of Geosciences, Georgia State University)[2] suggested a higher-order nearest neighbor function. Examining the average distance to two or three nearest neighbors rather than one nearest neighbor sometimes provides a different picture of a spatial distribution (personal communication, 6/28/2013). ArcGIS does not have higher-order (e.g., second-order, third-order, n^{th}-order) nearest neighbor analysis built-in, but the CrimeStat program[3] does.
- **Geoffrey Hewings** (Director, Regional Economics Applications Laboratory; Professor, Geography and Regional Science, University of Illinois)[4] suggested using a hierarchical metric to examine clustering at the census tract, community, and MSA levels (personal communication, 6/27/2013).
- **Bill Drummond** (Associate Professor, School of City and Regional Planning, Georgia Institute of Technology)[5] suggested using a standard deviational ellipse as follows: "the number of firms within the ellipse divided by the area of the ellipse" (personal communication, 6/26/2013).

[2] http://geosciences.gsu.edu/5078.html
[3] http://www.icpsr.umich.edu/CrimeStat/
[4] http://www.geog.illinois.edu/people/hewings
[5] http://www.planning.gatech.edu/people/william-drummond

He mentioned a recent paper that uses standard deviational ellipses: Yang et al. (2012).

- **Fred Shelley** (Professor, Department of Geography and Environmental Sustainability, University of Oklahoma)[6] suggested running the average nearest neighbor index and the standard deviational ellipse on nine sample regions from my dissertation proposal, then comparing the results. I did so, and we discussed my table before arriving at the average nearest neighbor distance as my key measure. I elaborate on this process below.

I selected my sample regions on the basis of the number of photonics firms. The nine sample regions are the metropolitan statistical areas with over 50 photonics firms (Table 3).

Table 3. Nine MSAs with over 50 photonics firms.

GEOID	MSA	Photonics Firms
35620	New York-Northern New Jersey-Long Island, NY-NJ-PA	260
14460	Boston-Cambridge-Quincy, MA-NH	242
31100	Los Angeles-Long Beach-Santa Ana, CA	222
41940	San Jose-Sunnyvale-Santa Clara, CA	150
16980	Chicago-Joliet-Naperville, IL-IN-WI	101
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	96
41860	San Francisco-Oakland-Fremont, CA	92
40380	Rochester, NY	89
41740	San Diego-Carlsbad-San Marcos, CA	73

[6] http://parker.ou.edu/~fshelley/

For each of these regions, I computed the average nearest neighbor index and the standard deviational ellipse. Table 4 shows the average nearest neighbor index results for these nine regions. All nine regions seem to be clustered using the index. But there are two problems with this metric: first, Darla Munroe advised against taking deviation from random as sufficient evidence for clustering, and second, the deviation from random in one study area is not comparable to the deviation from random in a different study area. However, the observed average nearest neighbor distance in miles *is* comparable across study areas, and it varies quite a bit between regions, as shown in Figure 3. Visually, there appear to be three groups:

1. Highly clustered: San Jose, at 0.49 miles on average from one firm to its nearest neighbor.
2. Mid-level clustered: Boston (1.13 miles), Los Angeles (1.21 miles), Rochester (1.25 miles), and San Diego (1.27 miles).
3. Not clustered: San Francisco (1.61 miles), New York (1.65 miles), Philadelphia (1.86 miles), and Chicago (2.17 miles).

Next, I compared these nine regions using the standard deviational ellipse as a metric of clustering. Table 5 shows the standard deviational ellipse numbers for these nine regions: the area of the ellipse, the number of firms in the ellipse, and the square miles per firm in the ellipse. This results in quite a different cluster ranking as compared to the average nearest neighbor distance, largely due to the differences in study areas. To illustrate the differences in study areas, I provide maps for each of my nine sample regions. Each map includes the metropolitan statistical area boundary, the boundary of the standard deviational ellipse, and the locations of photonics firms in the metropolitan statistical area. Figure 4 maps the ellipse for the New York City region, Figure 5 maps the ellipse for the Boston region, Figure 6 maps the ellipse for the Los Angeles region, Figure 7 maps the ellipse for the San Jose region, Figure 8 maps the ellipse for the Chicago region, Figure 9 maps the ellipse for the Philadelphia region, Figure 10 maps the ellipse for the San Francisco region, Figure 11 maps the ellipse for the Rochester region, and Figure 12 maps the ellipse for the San Diego region. The standard deviational ellipse metric of square miles per firm assumes that the firms are evenly distributed within the standard deviational ellipse, but as the maps show, this is not the case.

Table 4. Average nearest neighbor index for nine sample regions.

GEOID	MSA	Photonics Firms	Observed Mean Distance (Miles)	Expected Mean Distance (Miles)	Average Nearest Neighbor Index	z-score	p-value
35620	New York-Northern New Jersey-Long Island, NY-NJ-PA	260	1.65	2.54	0.65	-10.80	0.00
14460	Boston-Cambridge-Quincy, MA-NH	242	1.13	1.90	0.59	-12.07	0.00
31100	Los Angeles-Long Beach-Santa Ana, CA	222	1.21	2.34	0.52	-13.70	0.00
41940	San Jose-Sunnyvale-Santa Clara, CA	150	0.49	2.11	0.23	-18.00	0.00
16980	Chicago-Joliet-Naperville, IL-IN-WI	101	2.17	4.22	0.51	-9.34	0.00
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	96	1.86	3.46	0.54	-8.68	0.00
41860	San Francisco-Oakland-Fremont, CA	92	1.61	2.59	0.62	-6.93	0.00
40380	Rochester, NY	89	1.25	2.87	0.44	-10.18	0.00
41740	San Diego-Carlsbad-San Marcos, CA	73	1.27	3.80	0.33	-10.88	0.00

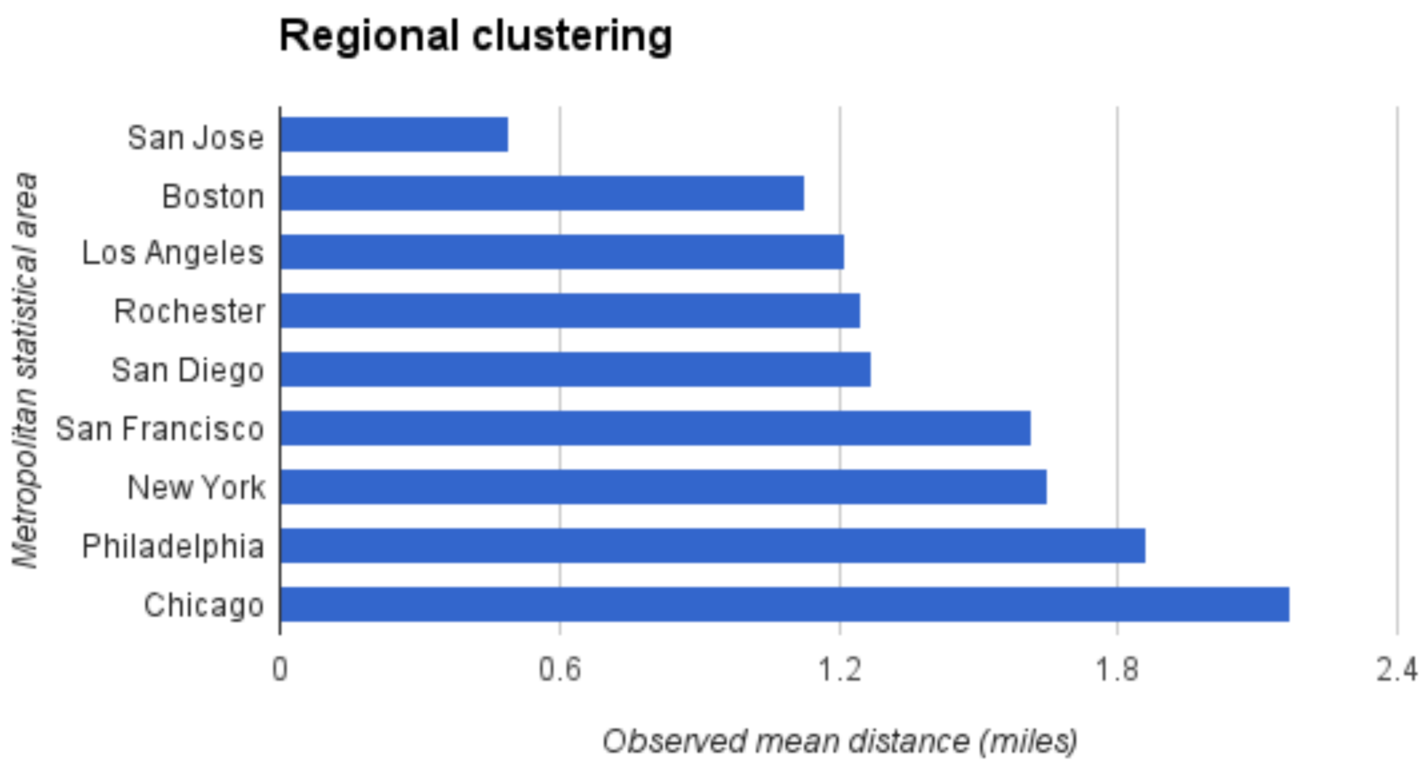


Figure 3. Average nearest neighbor distance in nine sample regions.

Table 5. SD ellipses for nine sample regions.

GEOID	MSA	Photonics Firms	Area of SD Ellipse (Square Miles)	Firms in SD Ellipse	Square Miles per Firm
35620	New York-Northern New Jersey-Long Island, NY-NJ-PA	260	2,502	157	15.93
14460	Boston-Cambridge-Quincy, MA-NH	242	1,050	165	6.36
31100	Los Angeles-Long Beach-Santa Ana, CA	222	1,136	140	8.12
41940	San Jose-Sunnyvale-Santa Clara, CA	150	112	109	1.02
16980	Chicago-Joliet-Naperville, IL-IN-WI	101	754	68	11.09
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	96	1,091	60	18.18
41860	San Francisco-Oakland-Fremont, CA	92	895	55	16.28
40380	Rochester, NY	89	372	69	5.39
41740	San Diego-Carlsbad-San Marcos, CA	73	307	51	6.01

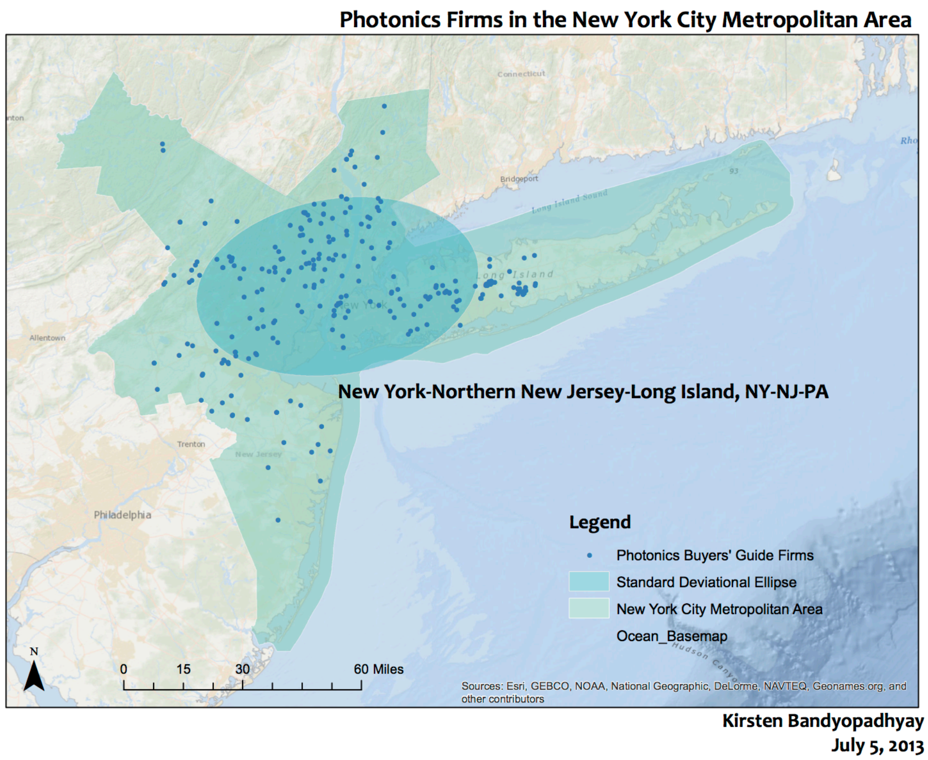
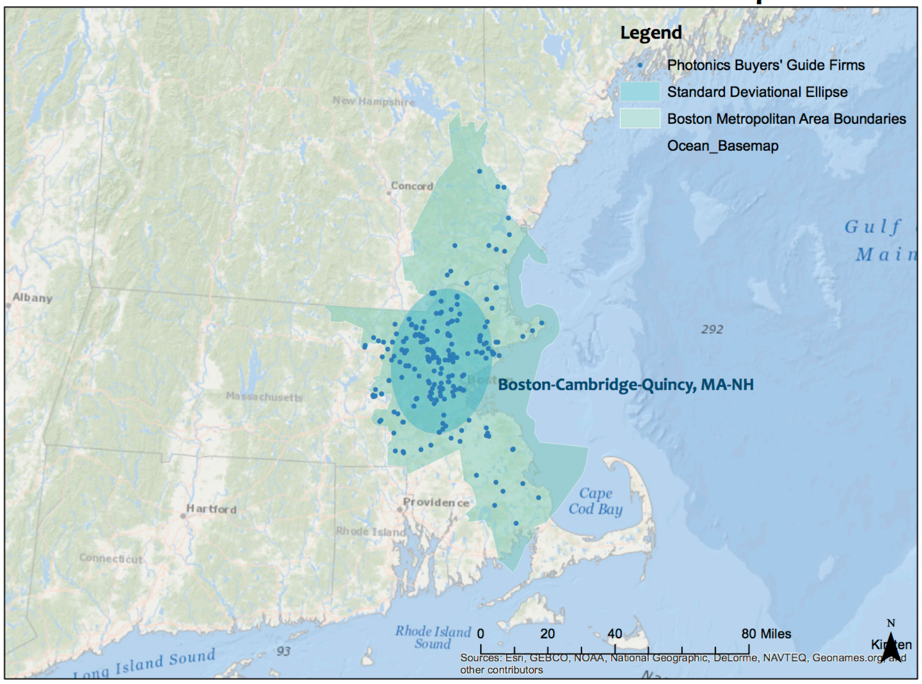


Figure 4. SD ellipse for photonics firms in the New York City region.

Photonics Firms in the Boston Metropolitan Area

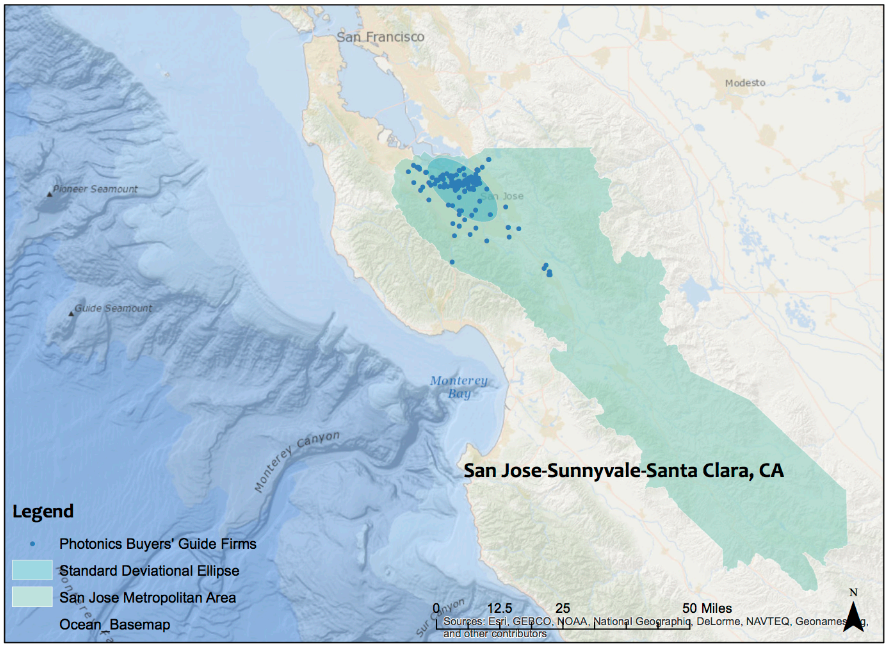


Kirsten Bandyopadhyay, 7/5/2013

Figure 5. SD ellipse for photonics firms in the Boston region.

Figure 6. SD ellipse for photonics firms in the Los Angeles region.

Photonics Firms in the San Jose Metropolitan Area (Silicon Valley)



Kirsten Bandyopadhyay
July 6, 2013

Figure 7. SD ellipse for photonics firms in the Silicon Valley region.

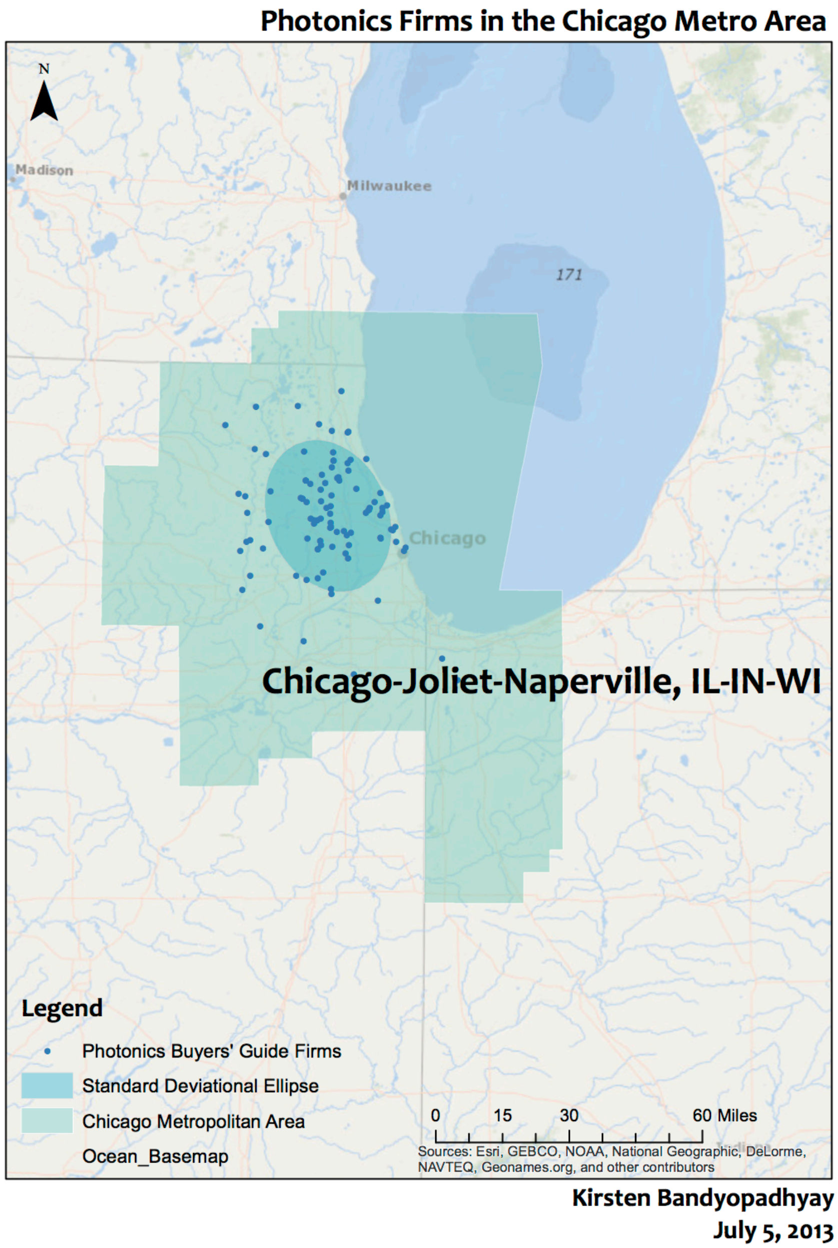


Figure 8. SD ellipse for photonics firms in the Chicago region.

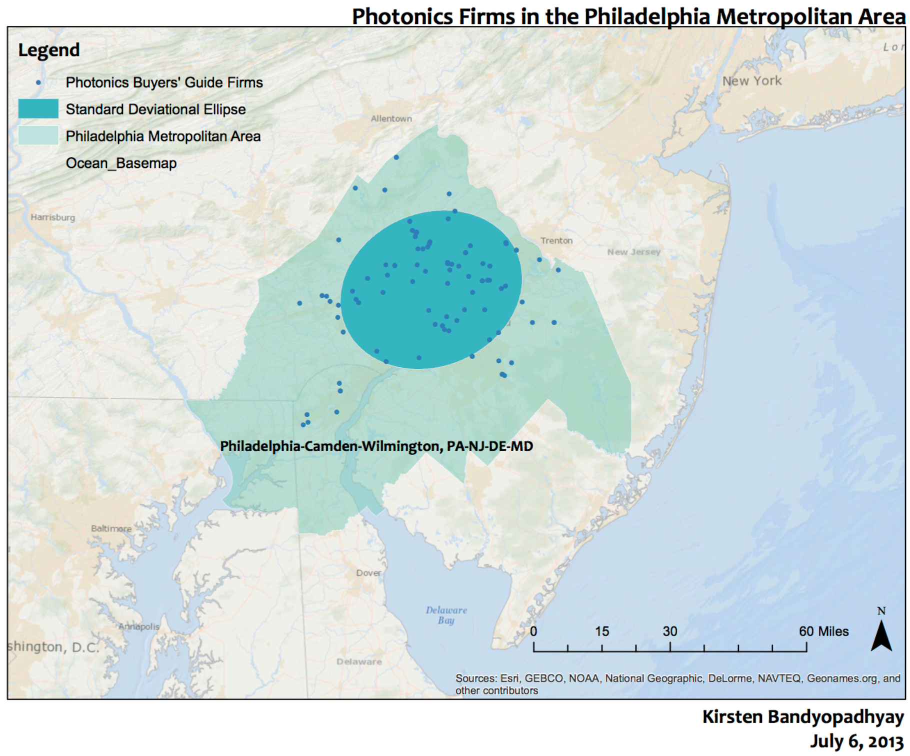


Figure 9. SD ellipse for photonics firms in the Philadelphia region.

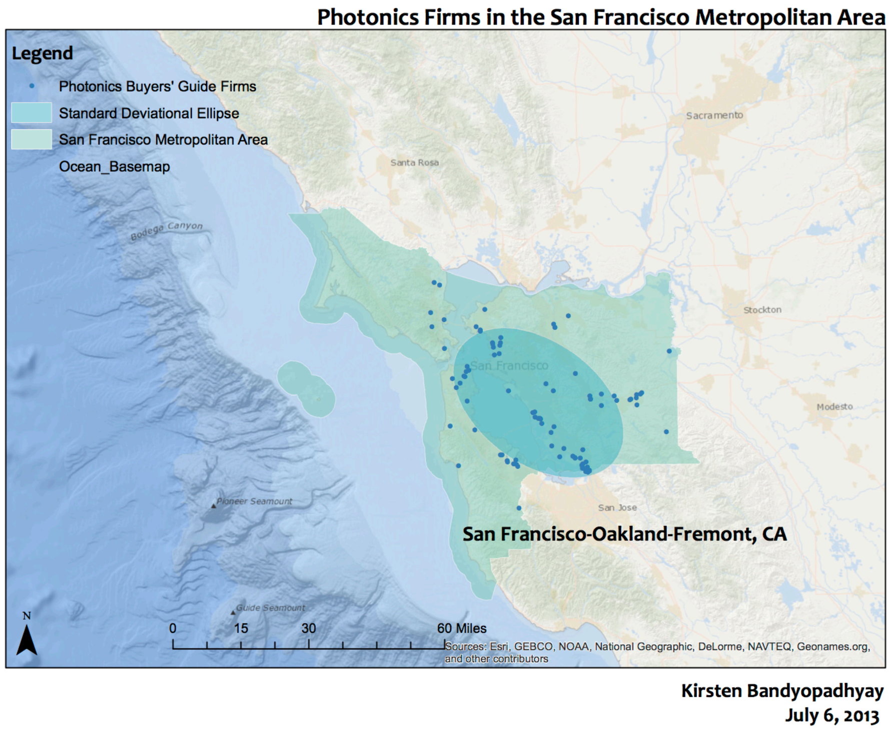


Figure 10. SD ellipse for photonics firms in the San Francisco region.

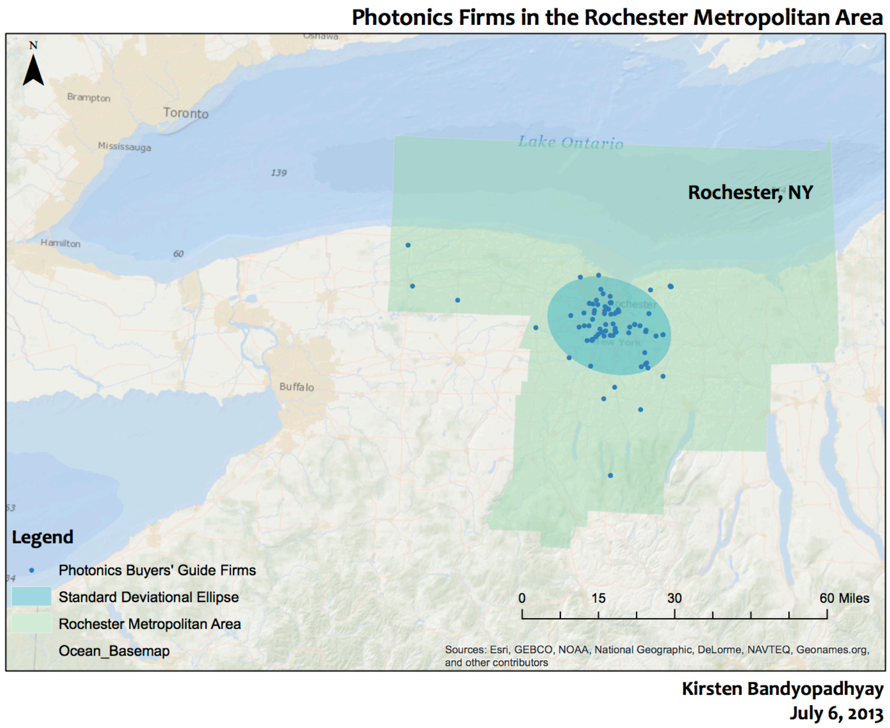


Figure 11. SD ellipse for photonics firms in the Rochester region.

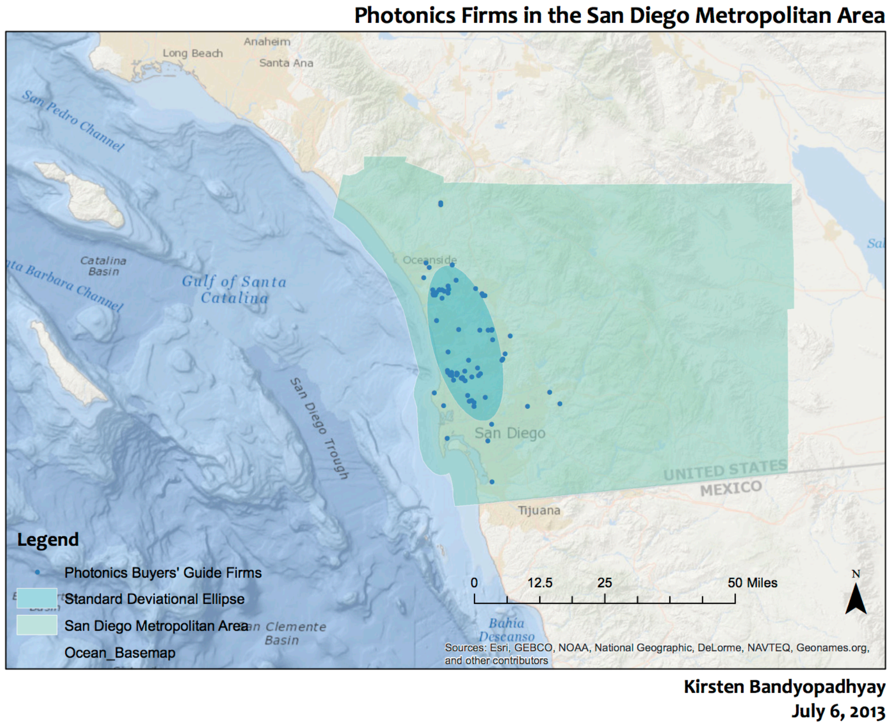


Figure 12. SD ellipse for photonics firms in the San Diego region.

After all of these comparisons, I selected the average nearest neighbor distance for two reasons. First, the average nearest neighbor distance is comparable across metropolitan areas. Unlike many other measures, the average nearest neighbor distance does not depend on a uniform study area. Second, the average nearest neighbor distance is more representative of the spatial distribution of firms in a metropolitan area as compared to the standard deviational ellipse, my second choice. Calculating the number of firms within the standard deviational ellipse divided by the area of the ellipse gives an approximation of firms per square mile, but this is misleading: firms are not evenly distributed within the ellipse, by definition. The average nearest neighbor distance shows how far, on average, an employee must walk from one company until she arrives at another company from the same industry. This metric makes no claims about an even spatial distribution of firms.

The average nearest neighbor distance is calculated as follows:[7]

1. Calculate the distance from one firm to all other firms in the region.
2. Record the smallest distance in that firm's record—this is firm *i*'s nearest neighbor distance.
3. Repeat for all other firms in the region.
4. Average the nearest neighbor distances for all firms in the region.

The Python script I wrote to calculate the average nearest neighbor distance for each MSA is in Appendix B. Table 6 shows descriptive statistics for the average nearest neighbor distance in all regions with at least 10 photonics firms.

[7] For more information on the average nearest neighbor distance, see Ebdon (1985). It is also quite common in public health: see Waller and Gotway (2004). And for a quick introduction, the ArcGIS 10.1 manual is quite helpful: http://resources.arcgis.com/en/help/main/10.1/index.html#/How_Average_Nearest_Neighbor_works/005p0000000p000000/.

Table 6. Descriptive statistics for clustering in regions with at least 10 photonics firms.

	Average Nearest Neighbor Distance in Miles
Minimum	0.37
Maximum	6.64
Mean	2.65
Median	2.50
Standard Deviation	1.47
N	52

Data sources: web scraped firms, an industry survey, and the Census

In this dissertation, I used three data sources. The first is a directory of photonics firms that I obtained by scraping the website of the *Photonics Buyers' Guide*, a leading trade publication for the industry.[8] The second is the 2010 Census, for both TIGER/Line metropolitan statistical area (MSA) boundary files[9] and County Business Patterns data[10] on the number of establishments per MSA. The third data source is a salary survey of a variety of professionals in the

[8] On the web at http://www.photonics.com/BuyersGuide.aspx, and also available as an annual print publication.

[9] TIGER/Line files and documentation for all years available here: https://www.census.gov/geo/maps-data/data/tiger-line.html. To download the 2010 files, go to https://www.census.gov/cgi-bin/geo/shapefiles2010/main, select "Core Based Statistical Areas" in the drop down for layer type, and click Submit. Then under "Metropolitan/Micropolitan Statistical Area (2010)" select "All states in one national file" and click Download.

[10] County Business Patterns data and documentation for all years available here: http://www.census.gov/econ/cbp/. To download the 2010 files, go to http://www.census.gov/econ/cbp/download/10_data/ and click the link for the Complete Metropolitan Area file.

photonics industry from around the United States.[11] SPIE, a leading photonics industry association, conducted the survey and then shared the raw data with Jennifer Clark and me.[12]

Web scraping for emerging industry firm-level data

Web scraping is a means of systematically extracting information from websites. For example, imagine you wanted to collect the names, titles, email addresses, and phone numbers of all of the faculty in public policy at Georgia Tech. You could create a spreadsheet in Microsoft Excel, manually open all of the faculty members' web pages, and type in the information for each one. Or you could write a program to do that for you: go to each website, search for name, title, email address, and phone number, and put that information into a spreadsheet. Web scraping is the programming approach. For this dissertation, I wrote my web scraping code in Python. But there are also tools that allow you to extract information from websites without writing code, such as import.io.

Firm-level data for emerging industries is notoriously hard to come by for three reasons. First, firm-level data that include specific firm addresses are scarce. Second, firm-level data through which firms can be categorized as belonging to an emerging industry are nearly impossible to obtain. Third, firms, like individuals, often consent to have their data reported only in aggregate in order to protect their privacy. I illustrate these challenges with an example.

[11] Here is SPIE's report on their 2012 salary survey: https://spie.org/Documents/CareerCenter/SalarySurveyAug12/SPIESalarySurveyReport2012.pdf.

[12] Find out more about SPIE at http://spie.org/.

In the United States, the Longitudinal Business Database (LBD)[13] covers establishment-level data for all businesses in the nation, but its access is restricted through the Census' Research Data Center Program.[14] More importantly for this dissertation, the LBD and similar datasets classify establishments by NAICS[15] industry code, and there is no specific NAICS code for photonics, as is the case for many emerging industries. Table 7 describes the two closest NAICS codes for photonics: 334413, "Semiconductor and Related Device Manufacturing," and 541712, "Research and Development in the Physical, Engineering, and Life Sciences (except Biotechnology)."[16]

[13] Longitudinal Business Database files and documentation for all years available here: https://www.census.gov/ces/dataproducts/datasets/lbd.html.

[14] For more information on the Census Bureau Research Data Centers Program, go here: https://www.census.gov/ces/rdcresearch/.

[15] NAICS stands for the North American Industry Classification System, a federal standard for classifying businesses in the United States. For more information, see http://www.census.gov/eos/www/naics/.

[16] Table compiled by searching for these NAICS codes on the Census NAICS tool at http://www.census.gov/eos/www/naics/.

Table 7. NAICS codes for photonics.

2012 NAICS Code	334413	541712
Title	Semiconductor and Related Device Manufacturing	Research and Development in the Physical, Engineering, and Life Sciences (except Biotechnology)
Description	This U.S. industry comprises establishments primarily engaged in manufacturing semiconductors and related solid state devices. Examples of products made by these establishments are integrated circuits, memory chips, microprocessors, diodes, transistors, solar cells and other optoelectronic devices.	This U.S. Industry comprises establishments primarily engaged in conducting research and experimental development (except biotechnology research and experimental development) in the physical, engineering, and life sciences, such as agriculture, electronics, environmental, biology, botany, computers, chemistry, food, fisheries, forests, geology, health, mathematics, medicine, oceanography, pharmacy, physics, veterinary and other allied subjects.
Photonics Index Entry within this Code	Photonic integrated circuits manufacturing	Photonics research and development services

This means that if I wanted to run specialization measures by metropolitan area for photonics, and if I wanted to measure the spatial clustering of photonics firms by metropolitan area, I would have to include all semiconductor firms (NAICS 334413), all non-biotech R&D firms (NAICS 541712), or both. In other words: there is no way to limit analyses to an emerging industry, or to any other industry that is not well-captured in the existing NAICS code structure.

So in this dissertation I used a different approach. I took a directory of firms in my target industry, photonics, and compiled the entries into a database that allowed me to run spatial statistics. The two key steps in this process were web scraping and geocoding. Each firm's entry in the *Photonics Buyers' Guide* includes the firm's name, address, founding year, number of employees, and facility square footage. In 2012, the *Photonics Buyers' Guide* listed 2,932 firms in the United States. I compiled these 2,932 firms into a spreadsheet by writing a Python script to scrape each firm's record from the *Photonics Buyers' Guide* website. The script is in Appendix A. I then geocoded these records in ArcGIS. Table 8 shows the descriptive statistics for these 2,932 firms.

Table 8. Descriptive statistics for *Photonics Buyers' Guide* Firms.

	Minimum	Median	Mean	Maximum	N
Year Founded	1773[17]	1987	1982	2012	2,681
Number of Employees	1	20	112	22,400	2,254
Facility Square Footage	120	12,000	40,090	5,760,000	1,883

Census TIGER/Line files and County Business Patterns

The *Photonics Buyers' Guide* provided firm-level addresses. When paired with two data sources from the Census, this web-scraped dataset allowed me to calculate the degree to which each metropolitan statistical area in the United States is specialized in photonics, and to what degree each metropolitan statistical area can be said to be highly clustered in photonics.

[17] This is not a typo. Reade Brothers Co., Ltd. was established in 1773 in Wolverhampton, England. The company, now named Reade International Corp., manufactures chemicals for pharmaceutical applications. http://www.reade.com/home/about-reade#Company_Historical_Highlights:

To find out how many photonics companies exist in each metropolitan statistical area (MSA) in the United States, I geocoded photonics firm records after web scraping them. The 2010 Census TIGER/Line shapefiles provide the boundaries for all Core Based Statistical Areas (CBSAs) in the United States. CBSAs include both metropolitan and micropolitan statistical areas; this dissertation focuses on metropolitan statistical areas (MSAs) because they cover 95% of all photonics firms. In short, this is an urban industry (Table 9).[18] To associate each firm record with an MSA, I performed a point-in-polygon spatial join in ArcGIS.[19]

Table 9. Photonics is an urban industry.

	Firms in these Areas	Percent of All Firms
Metropolitan Statistical Areas	2,771	95%
United States	2,932	100%

To calculate the percentage of firms in each metropolitan statistical area that are photonics firms, I used the total number of firms in each MSA from the 2010 County Business Patterns dataset. Establishments in the County Business

[18] Micropolitan statistical areas have an urban core of at least 10,000 inhabitants; metropolitan statistical areas have an urban core of at least 50,000 inhabitants.
[19] I used ArcGIS 10.1 for the spatial join, then exported the attribute table of the resulting layer to CSV for analysis in R.

Patterns are analogous to firms in the *Photonics Buyers' Guide*.[20] Table 10 provides descriptive statistics for the County Business Patterns establishments.

Table 10. Establishments and employment by geographical unit in the 2010 County Business Patterns.

	Areas Represented	Establishments	Employment
Metropolitan Statistical Areas	363	6,211,033	95,665,547
Micropolitan Statistical Areas	570	702,998	9,042,761
Core Based Statistical Areas	933	6,914,031	104,708,308
United States	1	7,396,628	111,970,095

The SPIE salary survey

Using the *Photonics Buyers' Guide*, the TIGER/Line MSA boundary files, and the County Business Patterns, I computed the degree to which each metropolitan area is specialized in photonics and the degree to which each metropolitan area's photonics firms are spatially clustered. The SPIE salary survey was used to test the effect of regional specialization and clustering on labor market outcomes. This dissertation focused on two labor market

[20] The County Business Patterns dataset defines establishments as follows: "An establishment is a single physical location at which business is conducted or services or industrial operations are performed. It is not necessarily identical with a company or enterprise, which may consist of one or more establishments. When two or more activities are carried on at a single location under a single ownership, all activities generally are grouped together as a single establishment. The entire establishment is classified on the basis of its major activity and all data are included in that classification." http://www.census.gov/econ/cbp/definitions.htm

The *Photonics Buyers' Guide* reports single locations of firms; in many cases, these are divisions of broader corporations that have a single function related to optics.

outcomes: employee wages and recruitment. I measured wages through a SPIE 2012 survey item ("What was your total 2011 annual pre-tax earnings at your current job, including all salary and bonuses?"). I measured employee recruitment through a SPIE 2012 survey item ("How did you find your current or original position at your present employer?"). The full salary survey instrument is in Appendix E. Table 11 shows the descriptive statistics for wages in the survey.

Table 11. Descriptive statistics for wages in the SPIE 2012 salary survey.

	Wages (SPIE 2012)
Minimum	$2,832[21]
Maximum	$800,000
Mean	$113,800
Median	$106,000
Standard Deviation	$56,895
N	3,278

Understanding how and why employees and employers find and value each other is a key area of study for both urban economists and labor geographers. In particular, the "How did you find your job?" item includes answer choices that allowed me to uncover the role of labor market intermediaries (SPIE 2012 survey):

[21] This is not a typo. It likely represents someone who worked only a few weeks in 2011. But since the survey data does not contain individual identifiers, I could not reach out to the respondent to ask.

How did you find your current or original position at your present employer? (select one)

- Printed job advertisement (newspaper or journal)
- Online job advertisement
- In-person job fair
- University career office
- Alumni network
- Professional association
- I was recruited
- Private placement agency
- Public/government placement agency
- Networking or referral through personal contact
- I contacted the employer directly (no job was advertised)
- Other ______________________________

Mark Granovetter's classic book, *Getting a Job: A Study of Contacts and Careers* (1995), showed that professionals find jobs in three key ways: via their social networks, by directly contacting an employer, and by using formal mechanisms—also known as labor market intermediaries (LMIs). LMIs are third-party services that match employees and employers, from executive search firms to temporary agencies to job boards and public sector workforce development programs. In this survey item, all but the last two options represent LMIs; the option "networking or referral through personal contact" represents social networks, and the option "I contacted the employer directly (no job was advertised)" represents direct contact. Granovetter finds that professionals rely most heavily on their social networks, while Benner (2002) and Saxenian (1996) find that LMIs are crucial in forging the connections that facilitate innovation in the electronics industry in Silicon Valley. It was thus interesting to discover (a) whether the photonics industry tilts more towards networking, direct contact, or LMIs as a whole and (b) whether these trends vary by regional specialization and firm clustering. Table 12 shows descriptive statistics for recruitment channels for the SPIE salary survey.

Table 12. Descriptive statistics for recruitment channels in the SPIE 2012 salary survey.

	Recruitment Channels
Social networks	29%
Direct contact	9%
Labor market intermediary	62%
N	3,269

Using the *Photonics Buyers' Guide*, the Census TIGER/Line boundary files and County Business Patterns, and the SPIE salary surveys, I constructed a rich dataset of photonics industry agglomeration and labor market outcomes by metropolitan area. In particular, I measured regional specialization, firm clustering, wages, and recruitment methods, along with a set of control variables for gender, education, years of experience, and employer size.

Analytical techniques

My research question relied on preliminary work showing that specialization and clustering are empirically distinct. In the preliminary work, I measured specialization and clustering in photonics for each metropolitan area in the United States, then created a regional typology of specialization and clustering. For good measure, I also ran correlations between my specialization and clustering metrics, and conducted a chi-square test on the regional typology. Once I established how specialization and clustering differ, I investigated the effects of specialization and clustering on wages and recruitment methods through a set of regressions and a pattern matching exercise (Yin 2014).

Preliminary work: Are specialization and clustering distinct?

Much of the literature on agglomeration uses the cluster concept—and that is fraught with conceptual and operational problems. I cut through the forest of conflicting effects of agglomeration by defining and measuring two very precise aspects of agglomeration: specialization and clustering. I used the standardized location quotient to categorize metropolitan statistical areas by their degree of specialization in photonics, and I used the average nearest neighbor distance for photonics firms in each metropolitan statistical area in the United States to categorize metropolitan statistical areas by their degree of clustering for photonics firms. The result is a table of all 363 metropolitan areas in the United States as of the 2010 Census, along with the following variables for specialization and clustering:

- Specialization
  - # of photonics firms in region
  - # of non-photonics firms in region
  - % of firms in region that are photonics firms
  - photonics location quotient for region
  - log of photonics location quotient for region
  - standardized location quotient for region
- Clustering
  - # of photonics firms in region
  - If >= 10 photonics firms in region:

- average distance from one firm to its nearest neighbor in miles

I then assigned each region a category of "low" or "high" for specialization and clustering according to the guidelines in Table 13. I used Table 14 to show how many regions fall into each category.

Table 13. Cutoffs for the regional typology of specialization and clustering.

	Specialization	Clustering
Low	SLQ <= 1.65	ANN distance <= 1.5 miles
High	SLQ > 1.65	ANN distance > 1.5 miles

I chose these cutoffs as follows. For specialization, since the standardized location quotient is a z-score, the 1.65 cutoff simply reflects the $p < .10$ guideline common in the social sciences. In the results chapter, I show how the SLQ cutoff compares with traditional location quotient interpretation guidelines. For clustering, Arzaghi and Henderson (2008) found that collaboration between advertising firms in Manhattan decayed significantly when those firms were located more than 750 meters apart. 750 meters is about half a mile—a ten-minute walk. In the strictest terms, I would only label a region high in clustering if *all* firms in the target industry were walking distance from at least one other firm. That is unlikely, which is why I used the average nearest neighbor distance: the central tendency provides room to identify a clustering trend even when one firm is located quite far from all other firms. Such an outlier will increase the average nearest neighbor distance, but its effect will lessen as the number of firms in the region grows.

If all regions in the United States were pedestrian-oriented regions, I would keep the walking distance cutoff. But they are not. The vast majority of metropolitan areas—and even central cities—in the United States are designed and built for driving. So I triple the clustering distance to 1.5 miles—about a ten-minute drive in medium to heavy traffic in a central business district.

While different clustering cutoffs result in different numbers of regions in each cell in my typology, the cutoffs do not fundamentally change my research findings. That is because the heart of my research is based on continuous values. In the preliminary work, I used a correlation coefficient to describe the relationship between specialization (measured as the standardized location quotient) and clustering (measured as the average nearest neighbor distance). For my research question, I used OLS regression to test the relationships between specialization, clustering, and wages; I used logistic regression and pattern matching (Yin 2014) to test the relationships between specialization, clustering, and recruitment methods. The only research finding that that changes based on the cutoffs is the pattern matching approach to analyzing the relationship between specialization, clustering, and recruitment methods; however, the logistic regression also tests this relationship and is not affected by a change in cutoffs.

In sum, yes, the clustering cutoffs are somewhat arbitrary. The purpose of the cutoff is to create a mental category for a policymaker to use. It is simply a heuristic—an exploratory tool. But the real results—the degree to which clustering is correlated with specialization, and the degree to which clustering affects recruitment and wages—rely on the continuous measure of the average nearest neighbor distance. The cutoffs have no impact on those results. In addition, my policy recommendations are based on the continuous results. All of which is to say that I defend my choice of cutoffs as a reasonable compromise for a thinking tool and address their somewhat arbitrary nature by using the continuous measures of clustering for testing effects and creating policy recommendations.

Table 14. Shell for the typology of specialization and clustering.

	Low specialization	High specialization
High clustering	# of regions	# of regions
Low clustering	# of regions	# of regions

If specialization and clustering were redundant measures of agglomeration, we would expect to see all regions in the "low specialization, low clustering" and "high specialization, high clustering" categories. In other words, we would not expect to find any instances of specialization in the absence of clustering (bottom right), or clustering in the absence of specialization (top left). To test the relationship between specialization and clustering, I calculated the Pearson correlation coefficient for the standardized location quotient and the average nearest neighbor distance. I also ran a chi-square test on the typology table above.

Research question: How do specialization and clustering affect wages and recruitment methods in science-based industries?

Policymakers pursue agglomeration strategies at least in part because they expect agglomerations to result in wage premiums and better firm-worker matching. Anecdotally, software industry veterans will tell you that the way to get paid more, find the best people to work with, and find the best companies to work for is to move to Silicon Valley. But we do not know whether these benefits are due to specialization, clustering, both, or neither.

As I mentioned in the section on data sources, I measured wages using a survey item that asks people to report their 2011 pre-tax earnings (salary and bonus only). I measured recruitment patterns using a survey item that asks people how they found their jobs. I then recoded the answer choices into Granovetter's (1995) three job-finding mechanisms: personal networks, directly contacting an employer, or labor market intermediaries.

To test the effects of specialization and clustering on wages, I ran a series of ordinary least squares (OLS) regressions on the log of wages. In keeping with standard labor economics practice, I used the log of wages because wages are not normally distributed. In each model, I controlled for employee education, years of experience, gender, and employer size—all variables present in my salary survey. The three models are as follows.

$$\log(wages) = b_0 + b_1 specialization + b_2 experience + b_3 education + b_4 gender + b_5 employersize + e$$

$$\log(wages) = b_0 + b_1 clustering + b_2 experience + b_3 education + b_4 gender + b_5 employersize + e$$

$$\log(wages) = b_0 + b_1 specialization + b_2 clustering + b_3 experience + b_4 education + b_5 gender + b_6 employersize + e$$

To test the effects of specialization and clustering on recruitment patterns, I ran a series of logistic regressions on whether an employee found their job using a labor market intermediary. In each model, I used the same controls as in the wage analysis. The three models are as follows.

$$\mathrm{LMI} = logistic(b_0 + b_1 specialization + b_2 experience + b_3 education + b_4 gender + b_5 employersize + e)$$

$$\mathrm{LMI} = logistic(b_0 + b_1 clustering + b_2 experience + b_3 education + b_4 gender + b_5 employersize + e)$$

$$\mathrm{LMI} = logistic(b_0 + b_1 specialization + b_2 clustering + b_3 experience + b_4 education + b_5 gender + b_6 employersize + e)$$

The variable specification for these models is presented in Table 15.

Table 15. Variable specification for regression models.

Concept	Operationalization	Data Source	Limitations
Wages	"What was your total 2011 annual pre-tax earnings at your current job, including all salary and bonuses?"	SPIE survey	Self-reported data could be wrong; no distinction between those who started work partway through the year and those who worked for a full 12 months
LMI	"How did you find your current or original position at your present employer? (select one)" 1 = Labor market intermediary choices (coded according to Granovetter (1995)) 0 = All other choices	SPIE survey	This is an employee sample rather than employer sample; no information about representativeness of the survey available
Experience	"How many years, total, have you been professionally employed? (select one)"	SPIE survey	This is ordinal rather than continuous (respondents select a category)
Education	"What is the highest educational level you have completed? (select one)"	SPIE survey	Not a perfect translation into years of education
Gender	"What is your gender? (select one)"	SPIE survey	Transgender, intersex, genderqueer, and otherwise non-binary individuals may be left out of a binary question
Employer size	"How many employees are in your organization (world-wide)? (select one)"	SPIE survey	This is ordinal rather than continuous (respondents select a category)
Specialization	Standardized location quotient	*PBG*, Census	The *Photonics Buyers' Guide* may be an incomplete directory of photonics firms
Clustering	Average nearest neighbor distance in miles	*PBG*, Census	The *Photonics Buyers' Guide* may be an incomplete directory of photonics firms

I also performed a qualitative analysis of recruitment methods using pattern matching as described in Yin's (2014) text on case study analysis. I illustrate this technique with H1: "High regional specialization increases the use of LMIs for recruitment if the number of firms in the region is also high (≥ 50)." For example, I would have rejected this hypothesis under any of the following conditions:

- A non-specialized region uses LMIs more than a highly specialized region, and the two have at least 50 firms each.
- The proportion of LMI use is the same in a specialized and a non-specialized region, and the two have at least 50 firms each.
- Highly specialized regions use LMIs more than a non-specialized regions in every case in my data, regardless of the number of firms.

On the other hand, I would not have rejected my hypothesis under the following pattern:

- Among regions with at least 50 firms each, the lowest proportion of LMI use in a highly specialized region will be greater than the highest proportion of LMI use in a non-specialized region.

This technique involved the possibility of both literal and theoretical replication. A literal replication of a finding would have occurred had I found that all highly specialized regions show the same recruitment patterns. A theoretical replication of a finding would have occurred had I found that all highly specialized regions differ systematically from all non-specialized regions in terms of recruitment patterns.

CHAPTER 4: RESULTS

Agglomeration captivates policymakers and academics alike. However, theoretical and empirical confusion around what counts as agglomeration has prevented researchers from testing the effects of agglomeration for both statistical and policy significance. In this dissertation, I have proposed that we study components of the agglomeration concept one at a time, starting with specialization and clustering. In the methods chapter, I shared my research question and hypotheses, explained how I measured specialization and clustering, and described my data sources and analytical techniques. In this chapter, I share the results: How distinct are specialization and clustering, really? How do specialization and clustering influence wages and recruitment patterns in scientific and technical labor markets?

Preliminary work: How distinct are specialization and clustering?

If we are to understand how different aspects of agglomeration truly affect labor market outcomes, it helps to first find out how the aspects in question relate to one another. Yes, specialization and clustering are both components of agglomeration—but to what degree do they overlap? Do all agglomerations exhibit both specialization *and* clustering? Or is it possible to identify a region specialized in an industry without much spatial concentration among its firms? Conversely, is it possible to identify a region with high firm clustering, but no recognizable specialization? Answering these questions provides the foundation for testing the effects of specialization and clustering on wages and recruitment patterns.

The distribution of specialization

Very few regions in the United States are specialized in photonics. Of the 363 metropolitan areas in the United States, 186 have at least one photonics firm. Figure 1 shows the locations of all 2,392 photonics firms in my data set within these 186 metro areas. Within these 186 regions, I measured specialization using the standardized location quotient (SLQ) as outlined in O'Donoghue and Gleave (2004) and explained in my methods chapter. In short, the SLQ is the z-score derived from the log of the location quotient. Table 16 illustrates the distribution of specialization in these regions.

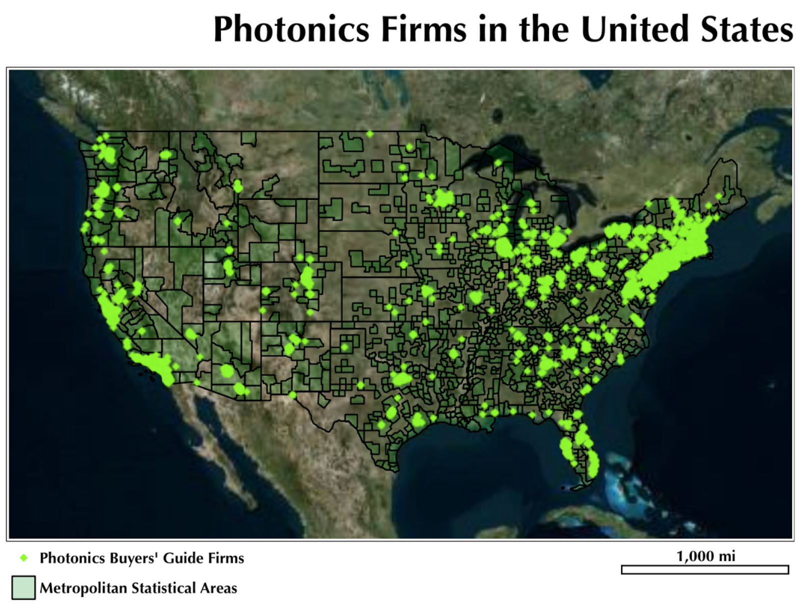


Figure 13. Photonics firms in US MSAs.

Table 16. Photonics specialization in US MSAs: SLQ.

Specialization	MSAs	Percent of MSAs
Low (SLQ ≤ 1.65)	173	93%
Mid (1.65 < SLQ ≤ 1.96) significant, *p* < .10, one-tailed	7[22]	4%
High (SLQ > 1.96) significant, *p* < .05, one-tailed	6[23]	3%
Total	186	100%

[22] Vineland, NJ (1.69), Oxnard, CA (1.78), Boston, MA (1.86), Worcester, MA (1.92), Tucson, AZ (1.93), Trenton, NJ (1.95), Ithaca, NY (1.95)

[23] Santa Barbara, CA (2.03), Boulder, CO (2.20), Ann Arbor, MI (2.23), San Jose, CA (2.43), Manchester-Nashua, NH (2.51), and Rochester, NY (2.56)

Only 3% of MSAs exhibit specialization in photonics (strict definition: $p < .05$), or 7% of MSAs (loose definition: $p < .10$). Figure 14 shows the histogram of the standardized location quotient across 52 metro areas.

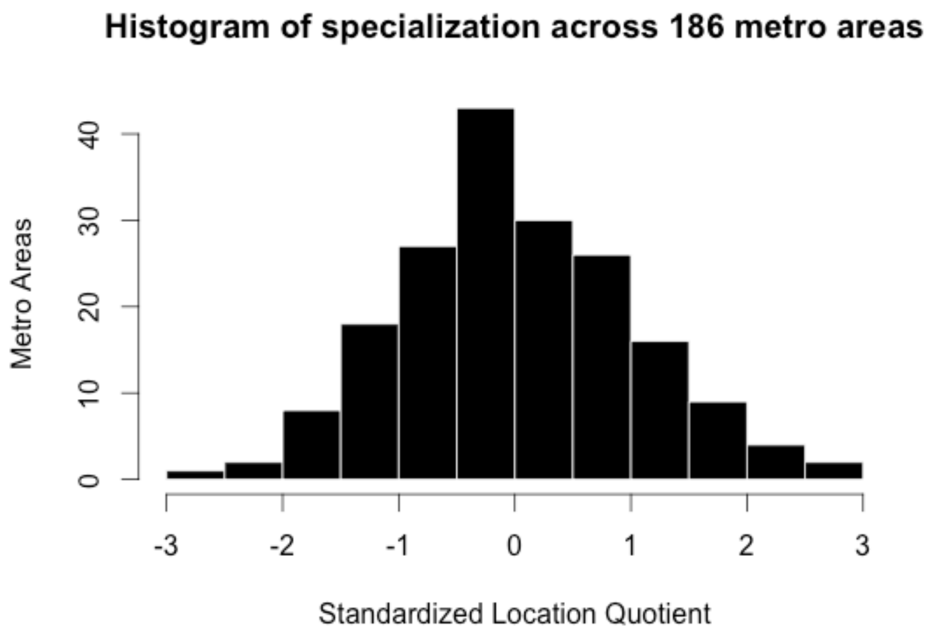


Figure 14. Histogram of specialization across 186 metro areas.

Only a small percentage of regions can be specialized by the definition of the SLQ, which computes specialization in comparison to other regions. Future research should compare the distribution of specialization in photonics with the distribution of specialization in other science and technology industries.

In standard economic development practice, a region is considered to have a specialization in a particular industry if its location quotient is above 1.25

(McLean and Voytek 1992). By this metric, 33% of the 186 metropolitan areas with at least one photonics firm can be regarded as specializing in the industry (Table 17). Or, if we consider specialization in all MSAs—even those without a single photonics firm—then 17% of 363 metropolitan areas can be regarded as specializing in the photonics industry. Figure 15 shows the histogram of the location quotient across 186 metro areas.

Table 17. Photonics specialization in US MSAs: LQ.

Specialization	MSAs	Percent of MSAs
Low (LQ ≤ 0.75): local-serving import substitution opportunity	84	45%
Mid (0.75 < LQ ≤ 1.25): local-serving producing enough to meet local demand	40	22%
High (LQ > 1.25): export-oriented producing enough for locals + exports	62	33%
Total	186	100%

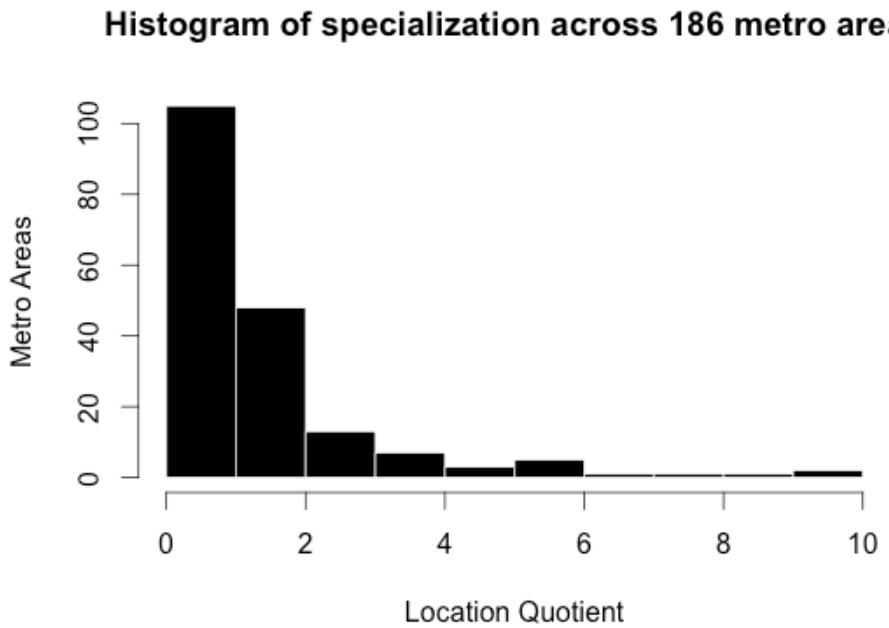


Figure 15. Histogram of location quotient across 186 metro areas.

However, the location quotient does not contribute to my goal, which is to identify the select few regions where photonics occupies an unusually large portion of the economy. In other words: of all the regions in the United States, which ones are photonics powerhouses?

Specialization is only meaningful when it discriminates between regions. If all of the MSAs in the United States are competing against one another, a metric that places 62 of them on the same footing is not a very useful ranking.

The SLQ captures this discrimination in two ways. First, it eliminates the asymmetrical nature of the location quotient by taking its log. The log of the LQ is normal. When working with a normal distribution, it is much easier to see where any region falls compared to its peers. Second, the SLQ identifies the top regions using a standard metric: the $p < .05$ cutoff of the social sciences. Since I was interested in extreme cases, the higher bar of the statistical test was more appropriate for the dissertation. Appendix D provides the traditional location quotient, the log of that location quotient, and the SLQ for all 186 metropolitan areas with at least one photonics firm.

In sum, 13 out of 186 metropolitan areas (seven percent) can be considered specialized in photonics under the $p < .10$ cutoff; 6 out of 186 metropolitan areas (three percent) can be considered specialized in photonics under the $p < .05$ cutoff.

The distribution of clustering

Clustering is less rare than specialization—at least among photonics firms in urban regions in the United States. Of the 363 metropolitan statistical areas in the United States, 52 have at least ten photonics firms. Within these 52 regions, I measure clustering using the average nearest neighbor distance. Table 18 shows the distribution of clustering in these regions, and Figure 16 provides the distribution in finer detail.

Table 18. Photonics clustering in US MSAs.

Clustering	MSAs	Percent of MSAs
Low (NN distance > 1.5 miles)	38	73%
Mid (0.5 miles < NN distance ≤ 1.5 miles)	12[24]	23%
High (NN distance ≤ 0.5 miles)	2[25]	4%
Total	52	100%

Only 4% of MSAs exhibit clustering in photonics (strict definition: NN distance ≤ 0.5 miles), or 27% of MSAs (loose definition: NN distance ≤ 1.5 miles). In other words, photonics firms in metropolitan areas that specialize in photonics do not tend to cluster closed to one another.

[24] Boulder, CO (0.64), Tucson, AZ (0.95), Trenton-Ewing, NJ (0.99), Santa Cruz-Watsonville, CA (1.04), Boston-Cambridge-Quincy, MA-NH (1.13), Santa Barbara-Santa Maria-Santa Goleta, CA (1.15), Manchester-Nashua, NH (1.18), Los Angeles-Long Beach-Santa Ana, CA (1.21), Rochester, NY (1.25), San Diego-Carlsbad-San Marcos, CA (1.27), Santa Rosa-Petaluma, CA (1.32), Ann Arbor, MI (1.38).

[25] Oxnard-Thousand Oaks-Ventura, CA (0.37), San Jose-Sunnyvale-Santa Clara, CA (0.49).

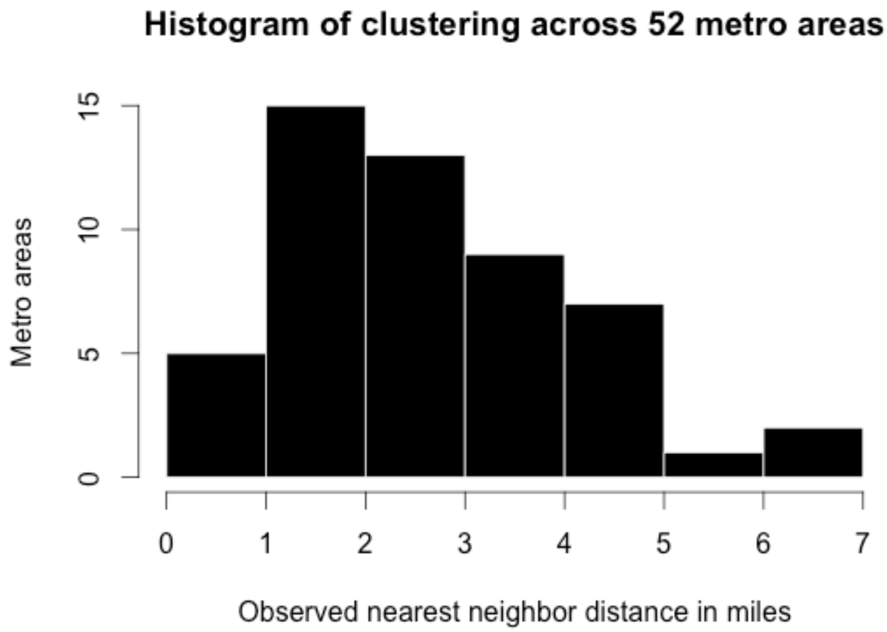


Figure 16. Distribution of photonics clustering among US MSAs.

The relationship between specialization and clustering

These results are consistent with the literature on agglomeration, which states that specialization and clustering are highly correlated but not always co-present. In a five cases, regions exhibit contrary trends: low specialization and high clustering, or high specialization and low clustering. Table 19 shows my typology of regions based on specialization and clustering. I tested the relationship between specialization and clustering with a chi-square test on the typology table, a categorical measure, and a correlation coefficient on the standardized location quotient and the average nearest neighbor distance, a continuous measure.

Table 19. Specialization and clustering typology.

	Low specialization	High specialization
High clustering	4[26] (8%)	10[27] (19%)
Low clustering	37 (71%)	1[28] (2%)

Specialization and clustering are related, whether measured categorically or continuously. Measured categorically, specialization and clustering are significantly related: *chi-squared* = 31.05, $p < .001$. Measured continuously, specialization and clustering and significantly related: $r = -0.78$, $p < .001$.

Given these results, does the agglomeration wage premium hold for specialization and clustering independent of one another? In other words: if we see higher salaries in regions with both high specialization and high clustering, which one is driving the effect? Is the wage premium due to specialization, clustering, both, or some other aspect of agglomeration not measured here?

Research question: How do specialization and clustering influence wages and recruitment patterns?

The key premise of this dissertation is that the definitional confusion around what constitutes agglomeration economies—theoretically and empirically—prevents us from testing the effects of different aspects of

[26] Santa Cruz-Watsonville, CA; Los Angeles-Long Beach-Santa Ana, CA; San Diego-Carlsbad-San Marcos, CA; Santa Rosa-Petaluma, CA

[27] Oxnard-Thousand Oaks-Ventura, CA; San Jose-Sunnyvale-Santa Clara, CA; Boulder, CO; Tucson, AZ; Trenton-Ewing, NJ; Boston-Cambridge-Quincy, MA; Santa Barbara-Santa Maria-Santa Goleta, CA; Manchester-Nashua, NH; Rochester, NY; Ann Arbor, MI

[28] Worcester, MA

agglomeration economies on outcomes that policymakers care about. In this dissertation, I narrow the scope to testing the effects of specialization and clustering on two labor market outcomes that policymakers interested in fostering high-tech labor markets care about: wages and recruitment methods. Table 20 provides an overview of my results.

Table 20. Results for the dissertation's research question.

	Hypothesis	Justification	Result
H1	High regional specialization increases the use of labor market intermediaries (LMIs) for recruitment if the number of firms in the region is also high (≥ 50).	Key studies of the electronics labor market in Silicon Valley highlight the role of LMIs like recruitment agencies, temporary labor firms, and professional associations in making the connections between employees and employers (Benner 2002; Saxenian 1996).	**Rejected.** LMI use is higher in a low specialization region (Chicago: 67%) than a high specialization region (San Jose: 55%), and they both have over 50 firms.
H2	High firm clustering decreases the use of LMIs for recruitment if the number of firms in the region is also low.	Close proximity facilitates information exchange (Arzaghi and Henderson 2008); workers in more tightly clustered firms should know more about job opportunities through their local networks and have less of a reliance on intermediaries.	**Supported.** the highest proportion of LMI use in a mid clustering region (Tucson: 46%) is lower than the lowest proportion of LMI use in a low clustering region (Washington DC: 47%).
H3	High regional specialization increases wages.	Competition among firms bids up the price of labor; previous studies find wage premiums in agglomerations.	**Partially supported.** Specialization increases wages only when we do not also take clustering into account.
H4	High firm clustering has no impact on wages.	The labor market for wage-setting extends beyond the neighborhood of nearest firms; overall MSA trends should have the biggest effect.	**Rejected.** Clustering increases wages, whether we take into account specialization or not.

How specialization and clustering affect wages

Employees often move to agglomerations in their industries to attain higher wages. Software engineers in Silicon Valley get paid more, even if the cost of living is higher. The question is whether the wage premium comes from specialization, clustering, both, some other aspect of agglomeration, or simply the cost of living. I found the wage premium is primarily a result of clustering.

This section illustrates the wage premium through both categorical and continuous measures of specialization and clustering. First, I examine mean differences in wages in high versus low clustering regions, and high-versus low specialization regions. Then, I explain the construction and the results of three regression models: the effect of specialization alone on wages, the effect of clustering alone on wages, and the effects of specialization and clustering on wages when taking both into account. I conclude this section with a discussion of the limitations of these models as well as proposals for future research to address those limitations.

Table 21. Summary statistics for wages in high versus low clustering regions.

Wages	High clustering	Low clustering
Min	$2,832	$3,000
Mean	$121,481	$114,804
Median	$118,000	$109,500
Max	$800,000	$480,000
Standard deviation	$63,533	$54,415
Regions	14	38
Employees	889	1,114

Table 21 shows that median wages are $8,500 higher in high clustering regions as opposed to low clustering regions. Mean wages are $6,677 higher in high clustering regions as opposed to low clustering regions. This difference is statistically significant ($t = 3.50$, $p < .001$). However, the data indicate that there are no significant differences between high specialization and low specialization regions (Table 22).

Table 22. Summary statistics for wages in high versus low specialization regions.

Wages	High specialization	Low specialization
Min	$13,000	$2,832
Mean	$122,241	$117,320
Median	$115,000	$110,000
Max	$412,000	$800,000
Standard deviation	$58,097	$59,113
Regions	11	41
Employees	670	1,333

Table 22 shows that median wages are $5,000 higher in high specialization regions as opposed to low specialization regions. Mean wages are $4,921 higher in high specialization regions as opposed to low specialization regions. This difference is *not* statistically significant at the 95% confidence level (t = 1.78, p = 0.08).

What if other factors are taken into account? In a series of multiple regression models, I included a set of control variables known to affect wages: years of experience in the workforce, years of education, employer size, and gender. Both years of experience and years of education represent an employee's skill set. Together, they form a subset of the concept of an employee's human capital. In general, people with more years of experience and more years of education make more money. Employer size, measured as the number of employees in the firm, represents the most salient aspect of a firm for determining wages. In general, larger firms pay more than smaller firms. And gender, though not related to skill, also affects wages, as we know from countless studies on the gender pay gap. Table 23 shows the results for each model.

Table 23. Three models for predicting the log of wages.

	Model 1: log(wages) ~ specialization + controls	Model 2: log(wages) ~ clustering + controls	Model 3: log(wages) ~ specialization + clustering + controls
Specialization (SLQ)	.03958 *	—	.005359
Clustering (average nearest neighbor distance in miles)	—	-.03488 *	-.03148 *
Years of experience	.02430 *	.02421 *	.02421 *
Years of education	.07020 *	.07019 *	.0724 *
Employer size	.00002134 *	.00002123 *	.00002126 *
Gender (male = 1, female = 0)	.1870 *	.1851 *	.1853 *
Intercept	9.656 *	9.768 *	9.755 *
Observations	1,988	1,988	1,988
R-squared	0.3334	0.3355	0.3356
F-statistic	198.3 on 5 and 1982 DF p-value: < 2.2e-16	200.2 on 5 and 1982 DF p-value: < 2.2e-16	166.7 on 6 and 1981 DF p-value: < 2.2e-16

Significance levels:

* p < .05

** p < .01

*** p < .001

These models do not differ in terms of explanatory power—the R-squared value does not vary much between them. While specialization and clustering are both significant predictors of wages when considered independently, when I add them both as predictors in model 3, only clustering is significant. So what do these effect sizes mean for salaries? Table 24 exponentiates the coefficients so that they are displayed in the units of wages—annual salaries in dollars.

Table 24. Effect sizes on wages for model 3: specialization and clustering.

	Estimate	e^Estimate	Significance
Specialization (SLQ)	.005359	1.005373385	
Clustering (average nearest neighbor distance in miles)	-.03148	0.969010336	***
Years of experience	.02421	1.024505441	***
Years of education	.0724	1.075085292	***
Employer size	.00002126	1.00002126	***
Gender (male = 1, female = 0)	.1853	1.20357946	***
Intercept	9.755	17240.21474	***

So, for example, when the average nearest neighbor distance increases by a mile, the average wage in the region declines by three percent—it becomes 97 percent of what it had been. By contrast, when an employee gains an additional year of experience, she can expect her wages to increase by 2.5 percent. What this means for our understanding of wages is that clustering, not specialization, seems to drive the agglomeration wage premium. If a policymaker is going after higher wages for scientific and technical labor, it makes more sense to encourage clustering by providing incentives to locate within a specific neighborhood than it does to encourage specialization by providing incentives to locate anywhere within a metro area.

That said, there are obvious limitations with this approach. First, this model only explains 33% of the variance in wages. The clustering wage premium could disappear if additional variables, such as the cost of living in a metropolitan area, could be taken into considering. Second, this is analysis is based on photonics data; the same trends may not hold in other science and technology industries. Third, this is based on a SPIE salary survey; SPIE salary respondents could differ from non-respondents in terms of skills, employment locations, gender, and wages. Fourth, I assumed that there is enough overlap in labor markets between SPIE salary survey employees and *Photonics Buyers' Guide* firms that using PBG firm data to measure clustering and specialization while predicting wages from the salary survey is reasonable. But I do not have any means to verify how much these two populations overlap. How do specialization and clustering affect recruitment patterns? Is clustering the primary driver? Or is it specialization, some combination of specialization and clustering, or neither?

How specialization and clustering affect recruitment patterns

For employees and hiring managers alike, one of the benefits of agglomeration is being able to find the right job or candidate faster. As Marshall (1920) wrote, agglomeration reduces the transport costs for people, including the search costs required to find the right colleagues and direct reports. If faster recruiting is a product of strong social networks and having the right kind of skill sets in the region, then specialization should have the bigger effect. But if faster recruiting is due to direct face-to-face contact, then clustering should have the bigger effect. I found that recruitment patterns do not differ based on clustering and specialization.

Table 25. Recruitment patterns in high versus low clustering regions.

How did you find your job?	High clustering	Low clustering
Networking or referral through personal contact	31%	30%
I contacted the employer directly (no job was advertised)	9%	8%
Labor market intermediary (includes I was recruited, alumni network, professional association, placement agency, career office, job fair, job ad, other)	59%	62%
N	889	1,114

Table 25 shows the distribution of recruitment patterns in high versus low clustering regions. A chi-square test confirmed that there is no statistically significant difference in recruitment methods between high and low clustering regions (*chi-squared* = 2.38, p = 0.30).

Table 26. Recruitment patterns in high versus low specialization regions.

How did you find your job?	High specialization	Low specialization
Networking or referral through personal contact	31%	30%
I contacted the employer directly (no job was advertised)	10%	8%
Labor market intermediary (includes I was recruited, alumni network, professional association, placement agency, career office, job fair, job ad, other)	59%	62%
N	670	1,333

Table 26 shows the distribution of recruitment patterns in high versus low specialization regions. A chi-square test confirmed that there is no statistically significant difference in recruitment methods between high and low specialization regions (*chi-squared* = 3.41, $p = 0.18$). Similarly, based on three binomial logit models—analogous to the models for wages, but with LMI use as the dependent variable—neither specialization nor clustering had an effect. Table 27 shows the results of these models. The coefficients are reported as odds, not log odds. None of the independent variables were significant; only the intercepts for models 1 and 3 were significant at the $p < .05$ level. As expected by the lack of significance among predictor variables, the models themselves lack explanatory power as measured by likelihood ratio tests, reported below for each model.

Table 27. Three models for predicting recruitment methods.

	Model 1: LMI ~ specialization + controls	Model 2: LMI ~ clustering + controls	Model 3: LMI ~ specialization + clustering + controls
Specialization (SLQ)	0.955		0.914
Clustering (average nearest neighbor distance in miles)		1.016	0.960
Years of experience	0.996	0.996	0.996
Years of education	0.986	0.987	0.986
Employer size	1.000	1.000	1.000
Gender (male = 1, female = 0)	0.902	0.902	0.899
Intercept	2.471*	2.250	2.814*
Observations	1,988	1,988	1,988
Likelihood Ratio Tests for Each Model			
chi-squared	2.846	2.033	3.293
degrees of freedom	5	5	6
p-value	0.724	0.845	0.771

This finding contradicts expectations from the literature on recruitment patterns in technology clusters. For example, a long history of work points to the uniquely flexible, fast-moving labor market as one key to Silicon Valley's innovative capacity (Benner 2002; Saxenian 1996). In flexible labor markets, highly skilled employees transition quickly between jobs in part due to their strong social networks.

Future research should examine the structure of social networks in different regions along the axes of specialization and clustering. For example: do the average sizes of networks differ substantially by region? How do people for ties? On average, do the proportions of strong and weak ties—which we know are important for finding a job (Granovetter 1995)—differ in high clustering versus low clustering regions? Further, *how* do people use their networks in their job searches? And do those networking strategies translate to better outcomes for individuals, firms, and regions? Given a sufficiently rich data set with social network data, clustering and specialization data, and human capital data, researchers can explore all of these questions.

CHAPTER 5: CONCLUSIONS AND POLICY RECOMMENDATIONS

Summary of problem and hypotheses

The purpose of this study was to evaluate the effect of specialization and clustering on the labor market strategies of small and medium-sized firms in science-based industries. To this end, I posed the following research question:

> RQ: How do specialization and clustering affect wages and recruitment methods in science-based industries?

This dissertation makes three key contributions to the research literature. The first contribution is theoretical: I disentangle specialization from clustering. While the two are correlated—Silicon Valley is the classic case in point—they are not identical. Distinguishing the effects of one from those of the other contributes to our understanding of the spatial segmentation of labor markets. In other words: who works where, and how does that segmentation affect our regional economies? Further, distinguishing specialization from clustering allows policymakers to make more informed decisions regarding recruiting companies to a metro area (a specialization strategy) versus recruiting companies into a tax-advantaged innovation district (a clustering strategy).

The second and third contributions are methodological: I provide a systematic method for cataloging the firms in a science-based industry, and then I calculate the spatial clustering of those firms by metropolitan statistical area (MSA). Rather than estimate the strength of an industry in a metropolitan area by virtue of a self-designated cluster association or survey responses, I offer a repeatable process to approximate the population of firms using web scraping and geocoding. This method is particularly valuable for industries that do not have a single category within federal statistical classification schemes such as NAICS (the North American Industry Classification System). Science policy researchers interested in emerging industries can use the web scraping and geocoding method detailed here to answer questions related to the spatial organization of firms those industries.

Similarly, rather than estimate the spatial clustering of an industry in a metropolitan area through a visual survey or a manual cataloging of firms, I offer a repeatable process to calculate the spatial density of firms using a variety of spatial statistics. After consulting with a number of spatial analysis experts and reviewing the literature on the topic, I chose to use an average nearest neighbor distance. Economic geographers interested in comparing the spatial clustering of firms across metropolitan areas—especially if they want a method they can use in regressions to test the relationship between spatial density and innovation outcomes—can use my review of the average nearest neighbor distance and other spatial metrics to select the indicator best suited to their needs.

Summary of methods used

I answered my research questions using two key methods: a spatial analysis of specialization and clustering and a set of regressions to examine the relationships among specialization, clustering, wages, and recruitment. In the spatial analysis, I used the standardized location quotient (SLQ) to measure specialization in the photonics industry, and I used the average nearest neighbor distance to measure the spatial clustering of photonics firms. In my regressions, I examined two key labor market outcomes: compensation and recruitment. I measured compensation as the annual wages paid in base salary and bonuses to photonics employees, and I measured recruitment methods through a survey question that asks photonics employees how they found their jobs. I controlled for education, years of experience, gender, and employer size.

Summary of data used

In my spatial analysis, I approximated the population of photonics firms by scraping entries on the 2,932 firms listed in the *Photonics Buyers' Guide*, a leading trade publication in the photonics industry. I collected the name, address, website, founding year, number of employees, and square footage of each firm, where available. I geocoded the firm records, then performed a spatial join with Census 2010 metropolitan statistical area boundary files to append the Census record for the metropolitan area within which the firm resides to the firm record. I then split the list of firms by metropolitan area, resulting in unique datasets of firm records by metropolitan area. I ran my spatial statistics—the standardized location quotient and the average nearest neighbor distance—on the metropolitan area datasets.

In my regressions, I used the 2012 SPIE salary survey to measure labor market strategies. The survey is also my source for control variables regarding education, work experience, gender, and employer size. SPIE is a leading trade association in photonics; respondents to the salary surveys have self-identified as working in photonics. I geocoded the survey responses, then performed a spatial join with Census 2010 metropolitan statistical area boundary files. I then joined the spatial statistics from my previous analysis to each survey response based on the metropolitan area from which that response arrived. I ran a set of regressions on the full data set of 3,161 responses from across the United States to examine compensation and recruitment trends nationally. That allowed me to pool regions with low response rates into larger categories so that I could test the effects of clustering and specialization on compensation and recruitment trends.

Summary of findings

This dissertation offers three key findings. First, regional specialization and firm clustering, while correlated, do differ. There exist regions that are specialized in the photonics industry but do not exhibit firm clustering, and there exist regions that have spatially dense clusters of firms but do not have enough firms within the context of the metropolitan area to count as specialized in any meaningful sense of the word. Future research should investigate how specialization and clustering separately affect innovation and economic development outcomes, such as patenting, firm revenues, regional growth, and so on. Future work should also replicate this study on other science and technology industries to determine whether photonics can be considered representative of high-tech industries in general.

Second, spatial clustering affects employee wages far more than regional specialization does. In fact, the wage increase for engineers associated with regional specialization disappears when we take clustering into account. When the average nearest neighbor distance in a metropolitan area decreases by one mile, the average wage for its photonics engineers increases by about $30,000. Future research should repeat this analysis in different science and technology industries while controlling for cost of living. If it holds, we have grounds for a fascinating qualitative study on what, exactly, firms are paying for—and how employees and their regions benefit from higher wages. Combined with research on the innovation and economic development outcomes associated with specialization versus clustering, this finding will help regional policymakers decide whether and how to encourage a particular industry.

Third, this dissertation suggests that place-based supports may be more important than people-based supports as a means of strengthening S&T labor markets. This follows from the finding that clustering, not specialization, drives the regional wage premium. Future research should replicate this study with other S&T industries, and measure labor market and innovation outcomes more directly.

Results: specialization, clustering, wages, and recruitment methods

The central research question of the dissertation is this:

RQ: How do specialization and clustering affect wages and recruitment methods in science-based industries?

To answer this question, I tested four hypotheses. Table 28 illustrates my results by hypothesis.

Table 28. Results by hypothesis.

	Hypothesis	Justification	Result
H1	High regional specialization increases the use of labor market intermediaries (LMIs) for recruitment if the number of firms in the region is also high (≥ 50).	Key studies of the electronics labor market in Silicon Valley highlight the role of LMIs like recruitment agencies, temporary labor firms, and professional associations in making the connections between employees and employers (Benner 2002; Saxenian 1996).	**Rejected.** LMI use is higher in a low specialization region (Chicago: 67%) than a high specialization region (San Jose: 55%), and they both have over 50 firms.
H2	High firm clustering decreases the use of LMIs for recruitment if the number of firms in the region is also low.	Close proximity facilitates information exchange (Arzaghi and Henderson 2008); workers in more tightly clustered firms should know more about job opportunities through their local networks and have less of a reliance on intermediaries.	**Supported.** the highest proportion of LMI use in a mid clustering region (Tucson: 46%) is lower than the lowest proportion of LMI use in a low clustering region (Washington DC: 47%).
H3	High regional specialization increases wages.	Competition among firms bids up the price of labor; previous studies find wage premiums in agglomerations.	**Partially supported.** Specialization increases wages only when we do not also take clustering into account.
H4	High firm clustering has no impact on wages.	The labor market for wage-setting extends beyond the neighborhood of nearest firms; overall MSA trends should have the biggest effect.	**Rejected.** Clustering increases wages, whether we take into account specialization or not.

This finding fits into the broader research literature on the mechanics of labor markets in science-based industries. Many researchers have studied how employers, employees, and labor market intermediaries interact; they are interested in what makes job markets competitive in a global economy and resilient in the face of economic shocks. This finding also addresses the research literature on the wage dynamics of high-tech industries. Plenty of economists have studied the returns to agglomeration economies in terms of regional GDP growth and the like; this study contributes an understanding of the returns to specialization and clustering from the perspective of employee wages.

In terms of the structure of labor markets, I found that specialization and LMI use are not related, but that clustering and LMI use are related. The strength of an industry in a region has little to do with how employees and employers find one another. Rather, the physical proximity of firms creates more opportunities for people to exchange information about job openings and candidates—at least when the number of firms is small. It would be fascinating to conduct a social network analysis of employees and firms in a science-based industry across several metro areas segmented by specialization and clustering. With that, we would be able to find out more about how information flows from one actor to another, and under which circumstances the environmental structures of specialization and clustering foster or inhibit that flow. In the absence of such a study, we are limited to generating hypotheses—not testing them.

In terms of the returns to employee wages on specialization and clustering, my findings suggest that proximity matters. When I controlled for spatial clustering, regional specialization had no impact on firm wages. Thus the spatial boundary for wage setting is not regional—it is local. In fact, it may be hyperlocal. In my study, I labeled regions highly clustered when the average distance from one firm to its nearest neighbor was less than half a mile—about 750 meters. That is walking distance. It is quite possible that the immediate neighborhood of a firm sets wage expectations far more than the metropolitan area, just as the immediate neighborhood of a building sets rents far more than the prevailing housing supply and demand in a broader metropolitan area. In fact, we may be able to take this analogy further: while the range of rents in a metro area is determined by the supply and demand of housing, which is why San Francisco is quite expensive, within that range actual rents vary immensely by neighborhood. Perhaps the range of wages in a metro area is determined by broader supply and demand factors in the labor market—number of employers for this type of technical labor, number of workers with these qualifications—but the actual offer a hiring manager makes to an employee varies immensely by immediate neighborhood. Do technical candidates interview with firms located walking distance from one another? When they use multiple offers to negotiate their salaries, do those offers come from spatially proximate firms? These are interesting questions to explore while taking into account the roles of employee education, experience, gender, employer size, and so on.

In sum, labor market intermediaries are less important in small, spatially clustered sets of firms. It makes intuitive sense: if 15 firms are within walking distance of each other, and everyone knows everyone, then job openings and candidates move quickly through the communication networks of the community without the need for placement agencies. This means policymakers trying to encourage a very small number of firms might put them all in a walkable "innovation district"—at least if the goal is for all the firms to be in the know about new developments as quickly as possible.

In addition, wages in areas packed with similar firms are much higher. What does that mean for employees? How do they use the funds they gain from working for a company in a cluster? And what does it mean for firms? What returns do they receive from paying more for technical labor? Maybe the labor is better; maybe the firms find more qualified candidates who produce better work. Maybe the firms have lower turnover. These are all questions for future research.

Discussion and research contributions

This dissertation makes three contributions to the research literature: one theoretical contribution and two methodological contributions. The theoretical contribution is to distinguish between specialization and clustering. I proposed that these are two distinct aspects of agglomeration, and my empirical findings show that while correlated, they are indeed distinct phenomena. This finding is of interest to economic geographers who study how labor markets work inside and outside agglomeration economies. It shows that it is possible to identify an industry concentration (specialization) without physical proximity (clustering) and vice versa, and suggests that specialization and clustering affect labor market outcomes differently. This finding is also useful for science and technology policy scholars who want to measure the strength of a given S&T industry in a metropolitan area. Now the proportion of employees or firms in the industry in an area—the location quotient—is not the only meaningful conceptualization of industry strength; S&T policy scholars can also consider the degree to which employees or firms in the industry in an area are clustered, an alternate conceptualization of industry strength, and one that matters for S&T labor market outcomes.

The dissertation's two methodological contributions are a systematic method for cataloging the firms in a science-based industry, and a repeatable process to calculate the spatial density of firms using a variety of spatial statistics. I showed how to use web scraping and geocoding—standard tools in programming and geography, respectively—to create a database consisting of the population of firms in a science-based industry. Ideally, researchers could find such a database through government statistics, but this is often impossible in emerging industries. With a little bit of Python and a lot of domain knowledge, it is possible to collect secondary data from sources that were previously inaccessible to many economic geographers.

Access to these sources opens up a variety of research possibilities on the spatial organization of firms and their connections to each other, which brings me to the second methodological contribution. In this dissertation, I measured the spatial density of firms using the average nearest neighbor distance, and I provided a list of a variety of alternative measures for other researchers to use. These spatial metrics are of interest to economic geographers and science and technology policy scholars who are interested in the spatial structure of S&T economies. While I used my spatial density measures to test the difference between specialization and clustering in labor market outcomes, they could be used in a host of research projects on how the geography of science develops and changes over time.

Research limitations

As all research projects do, this dissertation has both theoretical and empirical limitations. I begin with theoretical limitations. Rooted in evolutionary economic geography, this study was designed to test whether two aspects of agglomeration economies—specialization and clustering—are empirically distinct. An obvious limitation is thus the lack of attention to other aspects of agglomeration economies. As my literature review noted, economic geographers and science and technology policy scholars alike study the interactions between universities, firms, government institutions, and the intermediaries that connect them (Etzkowitz and Leydesdorff 2000). Further, these entities are connected in a variety of ways; physical proximity is but one of at least five types of proximity (Boschma 2005). It is possible that specialization and clustering patterns change dramatically when we take other institutions into account. It is also possible that measuring clustering along the axes of other types of proximity—cognitive, organizational, social, and institutional—would offer different theoretical implications for economic geographers and different policy avenues for policymakers.

My study has three key empirical limitations. The first is a concern about generalizability to other geographies and industries. This study is a proof of concept for distinguishing specialization and clustering in a science-based industry in the United States. Although I expect other researchers to find similar results in other science-based industries and other countries based on existing literature, it is impossible to know for sure until those studies are conducted. Perhaps the more interesting limitation is the lack of generalizability to industries outside science and technology. While science and technology industries are key drivers of economic growth and high policy priorities, they are not the only industries that states target for support. It would be fascinating to know whether similar patterns hold in non-S&T industries in which policymakers encourage investment.

The second empirical limitation is a concern about the use of proxies where more direct measurement would have been better. For example, I used the *Photonics Buyers' Guide* (PBG)—a widely respected trade publication—as my source of information on photonics firms. While the PBG is useful, it does not and cannot capture every single firm that participates in the photonics industry in the United States. Absent a comprehensive NAICS or similar classification, I argue that this is the best we can do. But a study on another science-based industry with a more comprehensive list of the population of firms would address this limitation. Similarly, I measured the strength of a labor market solely through wages. While wages have a long history in economic geography and econometrics as a labor market indicator, they are not the only indicator. Other indicators include the length of time it takes to find an S&T job, the vacancy rate for S&T occupations, the percentage of people with advanced degrees in S&T who are working outside S&T fields, and more. A useful source for these indicators at a more aggregate level is the NSF Science and Engineering Indicators, an annual publication available as both a report and a set of data tables.[29]

The third empirical limitation is a concern about the degree to which my disparate sources of data can be considered to measure the same thing. For example, I measured employee characteristics through the SPIE salary survey and firm locations through the *Photonics Buyers' Guide*. While SPIE is one of the largest industry associations in the world for photonics, and while the *Photonics Buyers' Guide* is a respected trade publication in photonics, there is no guarantee that the respondents to the SPIE salary survey work for firms listed in the *Photonics Buyers' Guide*. In other words, the spatial clustering characteristics of SPIE respondents' firms might actually differ quite a bit from the spatial clustering characteristics of PBG firms. The obvious way to fix this is with matched employer-employee data, a rare and valuable find for a researcher. I argue that in an emerging industry without NAICS or similar classifications, like photonics, this is the best we can do. But it would still be better to replicate this study on an industry with matched employer-employee data, to make sure that the clustering patterns for firms and the wage patterns for employees are indeed related.

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[29] NSF Science and Engineering Indicators 2014 available at http://www.nsf.gov/statistics/seind14/. For previous years, see http://www.nsf.gov/statistics/seind/.

Future research

My suggestions for future research derive directly from my discussion of limitations in the previous section. Thus I propose research to address the three empirical limitations and the two theoretical limitations.

To address the empirical limitations—generalizability to other industries and geographies, the use of indirect proxies, and the problems with disparate employer and employee datasets—I suggest the following projects. First, researchers can replicate this study in other industries, starting with S&T industries like biotechnology and software and then branching into more traditional industries as they come up in policy priorities. Second, researchers can replicate this study in other geographies. This might work in two ways: a direct replication in another country with clustering measured at the geographical unit most similar to our metropolitan statistical areas (MSAs), and a theoretical extension of this work that looks at how clustering metrics change at different geographical scales, such as zip codes, cities, counties, MSAs, states, and countries. Third, researchers can use better proxies. Especially if they choose more established S&T industries with better government records, they can find a more comprehensive directory of the population of firms in the target industry, then measure a broader set of labor market indicators to measure the health of the industry's labor market across all metropolitan statistical areas in the United States. This brings us to the fourth suggestion. If researchers can find a matched employer-employee dataset for an S&T industry, they can examine whether the S&T industry wage patterns in different regions are truly related to the specialization and clustering of the S&T industry in those regions.

To address the theoretical limitations—the absence of other institutions in S&T agglomerations and the absence of four other types of proximity—I suggest the following projects. First, using a matched firm-employee dataset for another S&T industry from above, select four regions from each specialization and clustering quadrant. Then, in those sixteen regions, conduct detailed case studies (Yin 2014) to show how the links between different institutions function to create S&T labor market outcomes in each region. Based on my research, I would expect the ways in which different institutions interact with each other to vary drastically based on regional specialization and clustering in the focal S&T industry. For example, I would expect social networks between different types of institutions to be much more dense in high clustering regions, with a concomitant increase in the speed with which regional actors pivot toward a new goal. Second, design a series of projects to assess the degree to which clustering along different axes of proximity—cognitive, organizational, social, institutional—shapes a broader set of S&T labor market indicators. These projects could be completely quantitative in nature, given sufficient secondary data and operational measures for each of these types of proximity. Or they could be woven into the case studies mentioned in my first suggestion. Either way, I would expect other forms of proximity to affect how actors in S&T labor markets relate to one another, and I would expect those changes to in turn influence S&T labor market outcomes.

Policy discussion

I discuss the policy implications of this dissertation through the lens of two broad policy categories: place-based supports and people-based supports. The debate about investing in places or in people dates to at least the 1960s, when (Winnick 1966) argued that place-based supports benefit some people who do not need support—for example, wealthy residents living in predominantly poor areas—and diverts investment from people in need located outside the place-based supports. On the other hand, people-based supports get the right resources in the hands of the right people. When they are well targeted, they do not leave anyone out, and they do not provide benefits to people who do not need them. From the 1960s through the 1980s, economists generally favored Winnick's view; indeed, even today, some argue that policymakers ought to forgo place-based supports in favor of people-based policies (e.g., Glaeser (2005)).

That said, contextually appropriate place-based supports work for three reasons (Fainstein and Markusen 1996). The first is that investing in places creates positive externalities in a variety of economic areas, from physical asset values to information circulation to overall labor market health. The second is that place-based supports further encourage the urban agglomeration economies that are at the core of Marshall's explanation of regional economic growth. And the third is that investing in physical infrastructure in existing urban cores prevents decline that is, in the end, more costly than ongoing maintenance.

The question, then, is not whether to invest in people or places, but under which circumstances to invest in each. Today, we realize that people-based supports are both more efficient and equitable for solving individual issues, and place-based supports are more efficient and equitable for solving public goods problems. Comprehensive urban policy portfolios include both.

In this section, I explore both place-based and people-based approaches for strengthening scientific and technical labor markets. While the literature on place-based and people-based approaches is largely in the realm of urban and economic development policy, I limit myself to policy supports for scientific and technical labor markets.

For that reason, I will not discuss enterprise zones or job training programs for chronically under- and unemployed workers. Enterprise zones are common place-based policy instruments with federal, state, and local history dating to at least the 1980s; the most recent manifestation of enterprise zones is the Obama administration's Promise Zone initiative.[30] In short, such zones aim to stimulate investment in blighted areas. They aim to create economic value where there is almost none. On the other hand, place-based supports in the world of scientific and technical labor markets aim to grow already existing investment in tech-heavy areas. For example, payroll tax exclusions in San Francisco for biotech, clean tech, and stock encourage local firms that are already thriving to grow

[30] To date, the Obama administration has launched two Promise Zone competitions. The press release for the second is available at http://www.whitehouse.gov/the-press-office/2014/09/19/obama-administration-launches-second-promise-zone-competition-create-eco, and more information on the initiatives is available through the Department of Housing and Urban Development at http://portal.hud.gov/hudportal/HUD?src=/program_offices/comm_planning/economicdevelopment/programs/pz.

even more.[31] They aim to expand economic value that is already booming. Similarly, job training programs for the chronically under- and unemployed are common people-based policy instruments with a long federal, state, and local history; Texas' Self-Sufficiency Fund[32] is but one recent example. Such programs aim to help people with minimal or no income develop the skills to obtain jobs that provide a living wage. Again, they aim to create a mechanism for generating economic value where there is almost none. On the other hand, people-based supports in the realm of scientific and technical labor markets aim to further strengthen already strong scientific and technical skills. For example, research and development tax credits in a variety of states encourage firms to invest even more in the innovative capacity of their research programs. Maryland in particular incentivizes rapid growth: the state offers a 10% tax credit on R&D expenses if those expenses are higher than average over the past four years, whereas expenses equal to or lower than the firm's four-year average are only eligible for a 3% tax credit.[33] Programs like these aim to make good S&T research and development into great S&T research and development.

People-based supports target upskilling and labor market reproduction. By nature, they are not place-specific. In other words, they are a specialization strategy. Place-based supports attempt to increase demand for labor in a

[31] A complete list of San Francisco tax credits, including these payroll tax exclusions, is available at http://sfgsa.org/index.aspx?page=4240.

[32] For more information on the Texas Self-Sufficiency fund, see http://www.twc.state.tx.us/svcs/funds/self-sufficiency-program-overview.html.

[33] For more information, see the Maryland Department of Business and Economic Development's page on R&D tax credits: http://business.maryland.gov/fund/programs-for-businesses/research-and-development-tax-credit.

particular neighborhood. In other words, they are a clustering strategy. To examine the implications of specialization and clustering on people-based and place-based supports, I sought to identify cases that met the following criteria.

- **The place-based case must illustrate attempts to increase demand for S&T labor among particular employers. The people-based case must illustrate S&T labor market upskilling and reproduction.** My findings about the relationships between specialization, clustering, wages, and recruitment methods have policy implications for increasing demand for S&T labor among particular employers, and for labor market upskilling and reproduction. The policy cases must offer an opportunity to illustrate these implications.
- **The S&T industries in both cases must be industries to which photonics may be generalized.** A key question for any S&T labor market study is to what degree the findings maybe generalized to other S&T industries. Photonics must be reasonably analytically generalizable to the industries in both cases.
- **The cases must be recognized in national media.** Both cases must have media coverage in at least two national outlets, such as *Fortune*, the *New York Times*, the *Wall Street Journal*, and similar publications.
- **The cases must be politically contentious.** Both cases must demonstrate value conflicts that cannot be resolved by further evidence of efficacy—or the lack thereof. In other words, they cases

must show “Should we do this?” conflicts rather than only “Does this work?” conflicts.

I did not limit my search to photonics cases because nationally recognized, politically contentious photonics cases are limited. While photonics is a big policy priority at both federal and regional levels, as the NNMI shows, it is a relatively unknown industry in the popular national media—which means it is also without a platform for addressing politically contentious value conflicts. Extending my search to other S&T industries allowed me to illustrate the policy implications of the dissertation with industries with which general readers are more familiar.

However, if future researchers would like to replicate this policy discussion with photonics cases, I would advise them to select those cases as follows. First, create a catalog of photonics policy initiatives in each of the 52 metropolitan areas with at least 10 photonics firms listed in this dissertation. Identify those policy initiatives by searching policy documents and news articles as well as conducting interviews with science and technology policymakers in each region. Then choose two to four of the identified initiatives to serve as case studies. Collect more in-depth information on each of those initiatives through both primary and secondary sources.

I argue that this level of detailed photonics discussion is not necessary because photonics is likely generalizable to a range of other science and technology industries, as shown in previous work (Clark 2013; Feldman and Lendel 2010). In the end, I selected two cases from the San Francisco metropolitan area: the Central Market and Tenderloin Payroll Tax Exclusion, also known as the Twitter tax break, and the rise of technology boot camps, ten-week private courses that prepare students for entry-level jobs in a variety of technical fields. These cases meet my criteria as follows.

- **The place-based case must illustrate attempts to increase demand for S&T labor among particular employers. The people-based case must illustrate S&T labor market upskilling and reproduction.** The place-based case, the payroll tax exclusion, illustrates an attempt to encourage technology firms such as Twitter to increase demand for S&T labor in the Central Market and Tenderloin area. The payroll tax exclusion only covers a few square blocks and was targeted at a handful of employers. The people-based case, technology boot camps, illustrates a new model for labor market upskilling and reproduction. Driven by market rather than policy demands, California regulators are struggling to catch up.
- **The S&T industries in both cases must be industries to which photonics may be generalized.** Both cases are drawn from the software industry, emblematic of the rise of technology and service jobs in the United States. Software, like photonics, is a platform technology: it is used in a variety of end markets, from defense to telecommunications to medicine.

- **The cases must be recognized in national media.** The Twitter tax break was covered in the *Wall Street Journal*[34], *Fortune*[35], *Forbes*[36], and *Bloomberg Business*[37], among others. The technology boot camp phenomenon was covered in *Business Insider*[38], *National Public Radio*[39], *Fortune*[40], and the *New York Times*[41], among others.
- **The cases must be politically contentious.** The Twitter tax break demonstrates a value conflict about the role of technology and gentrification in low-income neighborhoods populated by people of color. Evidence about the number or quality of jobs created as a result of the tax break cannot resolve this conflict. The technology boot camp phenomenon demonstrates a value conflict about the importance of technical education compared to other kinds of education, as well as all of the class and race tensions of the Twitter tax break. Evidence about the career achievements about boot camp graduates cannot resolve these conflicts. However, as I discuss in the

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[34] John Letzing, "Tax Breaks Pay Off in San Francisco," 8/29/2012, http://www.wsj.com/articles/SB10000872396390444506004577615253293219254

[35] Michal Lev-Ram, "Welcome to the Twitterloin, where tech-savvy cool meets gritty hood," 3/5/2015, http://fortune.com/2015/03/05/twitter-office/

[36] Tomio Geron, "The Twitter Tax and Zendesk: How Tech Companies Affect the City," 11/5/2012, http://www.forbes.com/sites/tomiogeron/2012/11/05/the-twitter-tax-and-zendesk-how-tech-companies-affect-the-city/

[37] http://www.bloomberg.com/news/articles/2014-04-03/twitter-tax-break-is-target-in-san-francisco-income-war

[38] Terence Chea, "Guy Spent $11,000 on a Coding 'Bootcmap' and Doubled His Salary," 4/12/2013, http://www.businessinsider.com/guy-spent-11000-on-a-coding-bootcamp-and-doubled-his-salary-2013-4

[39] Anya Kamenetz, "12 Weeks to a 6-Figure Job," 12/20/2014, http://www.npr.org/blogs/ed/2014/12/20/370954988/twelve-weeks-to-a-six-figure-job

[40] JP Mangalindan, "Can Silicon Valley boot camps get you a $120K job?" 10/10/2013, http://fortune.com/2013/10/10/can-silicon-valley-boot-camps-get-you-a-120k-job/

[41] Tamar Lewin, "Web-Era Trade Schools, Feeding a Need for Code," 10/13/2014, http://www.nytimes.com/2014/10/14/us/web-era-trade-schools-feeding-a-need-for-code.html

> boot camp case, the proliferation of boot camps aimed at specific gender, class, and racial groups offers one avenue toward resolution.

The remainder of this section is organized as follows. First, I examine place-based supports for scientific and technical labor markets, with a particular focus on payroll tax exclusions in technology districts. Second, I examine people-based supports for scientific and technical labor markets, with a particular focus on science and technology skill development initiatives for workers already employed in S&T fields. Third, I show how distinguishing between specialization and clustering changes our understanding of place-based and people-based supports for scientific and technical labor markets. I conclude with a call for future research.

Place-based supports

Place-based supports are designed to improve places and the connections between them. For example, improvements to physical infrastructure—such as roads, transit, and fiber optic cables—increase the economic value of a place. Land use policies are also place-based supports; zoning laws and allowed variances shape both the character and the economic potential of city neighborhoods.

In the world of science and technology labor markets, one of the most recent examples is the “Twitter tax break” in San Francisco. This is a payroll tax exclusion covering a few square blocks in the Tenderloin and central Market

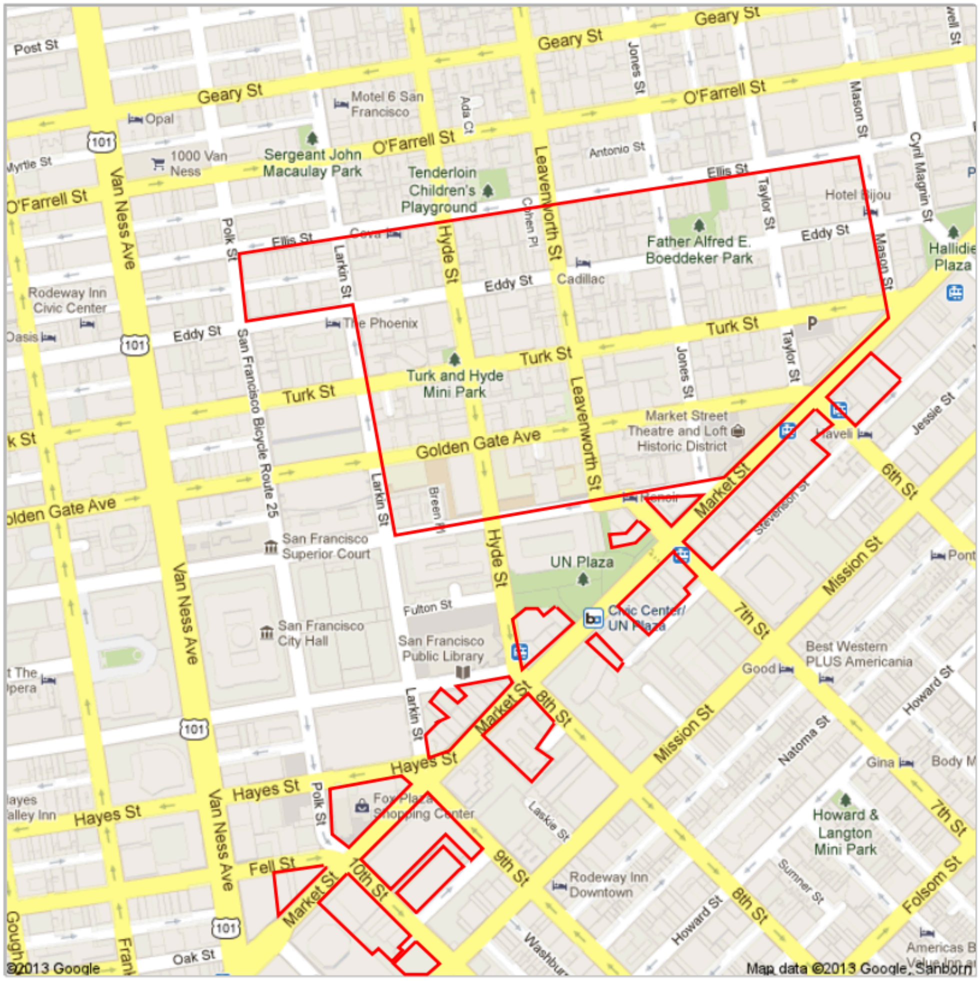
Street area (Figure 17).[42] Companies that located within the neighborhood covered by the exclusion were allowed to continue to pay their 2011 payroll tax bill, even as they added new employees in the following years.[43] A recent report by the Office of Economic Analysis in the City and County of San Francisco found that the three-year rate of job growth in the tax exclusion area was more than double that of the city as a whole during the same period.[44] On the other hand, real estate values did not increase at a higher rate than in the rest of the city, and sales taxes actually increased at a lower rate than in the rest of the city.

[42] Boundary map courtesy of the City and County of San Francisco Office of Economic and Workforce Development: http://www.oewd.org/modules/showdocument.aspx?documentid=235.

[43] The legislative text for the Central Market/Tenderloin Payroll Tax Exclusion is available at http://www.oewd.org/modules/showdocument.aspx?documentid=236.

[44] Read the report, "Review of the Impact of the Central Market Payroll Tax Exclusion," published in October 2014, at http://sfcontroller.org/Modules/ShowDocument.aspx?documentid=5914. It is especially interesting in comparison to the forecasted economic impact report, "Payroll Expense Tax Exclusion in Central Market Street and Tenderloin Area," from March 2011, just before the legislation was passed.

Central Market Street and Tenderloin Area Payroll Tax Exclusion Boundary Map



The properties outlined in red are included in the exclusion zone. This map is for informational purposes only.

To verify the eligibility of a property begin by looking up the block and lot number of your location here. Then confirm it is on the list of approved block and lot numbers listed in Section 906.3(b)(1) here.

Figure 17. Boundary map for the Central Market and Tenderloin Area Payroll Tax Exclusion, from the City and County of San Francisco Office of Economic and Workforce Development.

This sounds effective, but the economic impact of the payroll tax exclusion depends on whether the companies that located within the central Market Street area would have located in San Francisco anyway. If yes, then the tax exclusion is a net loss—the city is missing out on all the revenue that would have been collected had payroll tax bills continued to rise as companies continued to hire more workers. If no, then the tax exclusion is a net gain—the revenue collected from 2011 to 2014 is compared to zero, the amount the city would have obtained had all of the companies that located within the tax exclusion zone moved out of the jurisdiction of the City and County of San Francisco. In other words: it is impossible to prove a counterfactual. Who can say that these companies would have moved out of San Francisco without the payroll tax exclusion? Any answer can only be speculation.

Nonetheless, the payroll tax exclusion is an excellent example of a place-based policy. And it is quite controversial.[45] Before it was implemented, advocates for the payroll tax exclusion argued that it would redevelop a lackluster area of Market Street, that it would add technology jobs, and that it would prevent key technology firms (including, but not limited to Twitter) from leaving San Francisco, thereby damaging the local S&T labor market.[46] Opponents of the payroll tax exclusion argued that it would damage San

[45] See the city's main paper reporting on the issue by Rachel Gordon, "SF's Twitter tax-break plan spurs political fight," March 20, 2011 at *SFGate*. http://www.sfgate.com/politics/article/SF-s-Twitter-tax-break-plan-spurs-political-fight-2387943.php.

[46] See an op ed in favor of the tax break by Randy Shaw, "Landmark measure would revitalize SF's mid-market and uptown Tenderloin" in *Beyond Chron*, from February 8, 2011 at http://www.beyondchron.org/landmark-measure-would-revitalize-sfs-mid-market-and-uptown-tenderloin/.

Francisco's already struggling city finances, and that companies valued at over $1 billion do not need any tax relief.[47]

Three years later, it is hard to tell. No one can know for sure how many companies would have moved but chose to stay. In other words, policies like these offer uncertain risks and benefits (Barke 2009)—and policymakers and participants in political conversations around these policies alike must assess potential and actual outcomes in spite of this uncertainty. Advocates continue to praise the payroll tax exclusion,[48] and opponents continue to vilify it.[49] It makes sense: policy positions are as much a product of political and social values as they are about any economic impact analysis, even among scientists (Silva, Jenkins-Smith and Barke 2007). In this case, the key values at stake are technological progress and social justice. Encouraging technology jobs in the name of progress often conflicts with the desire to provide opportunities and advancement for all social groups, including those underserved by existing power structures. But these do not always conflict. As the next section shows,

[47] For example, see Bruce Brugmann, "No tax breaks for Twitter," a February 1, 2011 opinion piece on a blog hosted by the paper *San Francisco Bay Guardian*. http://www.sfbg.com/bruce/2011/02/01/editorial-no-tax-breaks-twitter. The *San Francisco Bay Guardian* (no longer publishing new issues, but the website still lives) and *Beyond Chron*, both self-identified progressive publications, hate each other; for a sample of their arguments, see http://www.sfbg.com/politics/2011/02/11/why-payroll-tax-breaks-are-stupid.

[48] For example, Bob Linschield, the president and CEO of the San Francisco Chamber of Commerce championed the payroll tax exclusion as "a key driver in the area's comeback," and said the SF Controller's economic impact report showed "the effect is proving positive"—even though it is impossible to prove the counterfactual that Twitter would have left in the absence of the tax exclusion. Read Linschield's op-ed at http://www.sfexaminer.com/sanfrancisco/comeback-for-central-market-spurred-by-tax-incentive/Content?oid=2697681.

[49] For example, the Service Employees International Union (SEIU) Local 1021 has been protesting the Twitter tax break since the beginning. On April 15, 2014, they marched to Twitter to deliver a bill for the taxes the company would have paid from 2011 to 2014. See http://nextcity.org/daily/entry/san-francisco-union-seiu-twitter-tax-day-protest-break for more details.

technical boot camps targeted at underserved and underrepresented populations have begun to emerge. And that leads us to people-based supports.

People-based supports

Rather than focus on specific geographical areas, people-based supports are designed to improve people and the connections between them. For example, building networking infrastructure—such as fostering relationships between actors in universities, industry, and government—is a common policy strategy in innovative regions. STEM education policies are also people-based supports: K-12 and higher education form the backbone of skill development for the next generation regional workforces, and are thus a key element of S&T labor market reproduction.

In science and technology labor markets, one of the more interesting recent trends is that of technology boot camps.[50] In approximately ten weeks, these courses promise to produce graduates capable of taking entry-level positions in technical roles from developer to product designer to data scientist. For example, General Assembly's Web Development Immersive includes not only technical fundamentals but also introductions to local development teams and portfolio preparation.[51] At about $15,000 per course, boot camps do not come cheap. But they do offer a new model for labor market upskilling in rapidly

[50] For example, see the *Fortune* article, "Can Silicon Valley boot camps get you a $120K job?" at http://fortune.com/2013/10/10/can-silicon-valley-boot-camps-get-you-a-120k-job/, the *Associated Press* article reprinted by *Business Insider*, "Guy Spent $11,000 on a Coding 'Bootcamp' and Doubled His Salary" at http://www.businessinsider.com/guy-spent-11000-on-a-coding-bootcamp-and-doubled-his-salary-2013-4, and *NPR* Education's blog post, "12 Weeks to a Six-Figure Job" at http://www.npr.org/blogs/ed/2014/12/20/370954988/twelve-weeks-to-a-six-figure-job.

[51] https://generalassemb.ly/education/web-development-immersive

changing conditions. The financial models differ as well. While some boot camps require payment up front, others accept a portion of graduates' first year salaries as payment—which means graduates who do not find jobs in technology do not pay any tuition. Further, boot camps targeted at women, people of color, and other underserved communities attempt to reconcile value conflicts between technological progress and social justice. In San Francisco, Hackbright Academy runs a trans-inclusive coding boot camp for women, and CODE2040 focuses on bringing black and latino/a engineering talent into technology. In Washington, DC, Code for Progress offers coding fellowship programs for women and people of color. Such initiatives now extend to youth, too: Black Girls Code is one example. Yes We Code offers a directory of such initiatives around the nation.

How technology boot camps fit into the broader landscape of upskilling and labor market reproduction in S&T labor markets remains to be seen. So far, they have been driven by market rather than policy demands; the boot camps are privately run organizations, not accredited educational institutions. That may change. In January 2014, the California Department of Consumer Affairs' Bureau for Private and Postsecondary Education (BPPE) sent cease-and-desist letters to several technology boot camps in San Francisco.[52] The argument is that as providers of vocational education, technology boot camps can and should be regulated as such. For example, the BPPE wants to ensure that performance claims on boot camp websites—such as the percentage of

[52] See Christina Farr, "California regulators seek to shut down 'learn to code' bootcamps" at http://venturebeat.com/2014/01/29/california-regulator-seeks-to-shut-down-learn-to-code-bootcamps/.

graduates that are employed in technology, and the average salaries of graduates from each course—are based on accurate, independently verified numbers.[53] Whatever happens with the regulation and oversight of technology boot camps in San Francisco, their existence raises questions about how policy might address upskilling and retooling for S&T workers across the educational spectrum. After all, not all S&T jobs require advanced degrees. One report suggests that up to 50% of all S&T jobs do not require a four-year degree (Rothwell 2013).

Obviously, people live and work in particular places. That is the premise of relational economic geography: both economic activity and the relationships that make economic action possible are unevenly distributed across space and time. Yet the distinction between place-based and people-based policy still holds. The primary focus of place-based policy is strengthening a particular place; the primary focus of people-based policy is strengthening a particular set of people (or organizations). When the goal is to strengthen a set of people in a particular place—for example, to improve S&T skills in a particular neighborhood—both place-based and people-based policies may be used in tandem.

Industry supports are a special case of people-based policies. Policies that offer incentives to particular industries—such as film tax credits in Georgia[54]—

[53] See Selena Larson, "Why coding boot camps should be regulated," at http://readwrite.com/2014/02/18/why-coding-bootcamps-should-be-regulated.

[54] For more detail on Georgia's film tax credits, see the Georgia Department of Economic Development's page at http://www.georgia.org/industries/entertainment/production-incentives/. For an overview of film tax incentives across all 50 states, see the National Conference of State Legislature's 2014 report, "State Film Production Incentive Programs," at http://www.ncsl.org/Portals/1/Documents/fiscal/2014FilmIncentivePrograms.pdf.

attempt to attract and retain a set of people, where the set is defined by industry rather than by education or another attribute. Emerging industries like biotechnology and nanotechnology often become policy targets; more recently, with innovations in additive manufacturing, advanced manufacturing has become a target for forward-looking regions.

As another example, Arizona,[55] Minnesota,[56] North Carolina[57] and Texas[58] offer tax incentives for companies that locate data centers in their states. In North Carolina, large data centers that invest in both real and personal property are "exempt from sales and use taxes on machinery and equipment." What counts as "large" depends on the county; in richer counties, "large" means a minimum investment of $300 million in real and/or personal property, while in poorer counties, "large" means a minimum investment of $150 million in real and/or personal property.

As a general principle, policymakers use industry supports to attract economic activity that is projected to grow quickly in the future. They use other people-based supports to develop the skills necessary to support employers in target industries. And they use place-based supports to redevelop declining neighborhoods and increase their brand and market value as great places to live and work.

[55] More details via the Arizona Commerce Authority: http://www.azcommerce.com/incentives/computer-data-center-program.

[56] More details via the Minnesota Department of Employment and Economic Development: http://mn.gov/deed/business/locating-minnesota/incentives/, under the "Industry Incetives" tab.

[57] More details via the Charlotte Regional Partnership: http://charlotteusa.com/business-info/costs-of-doing-business/.

[58] More details via the Austin Chamber of Commerce: http://www.austinchamber.com/site-selection/taxes-incentives/incentives/.

We know from the policy evaluation literature that industry supports tend to work better for regions that already have some kind of core competence in the industries they target for policy intervention. It is easier to grow an existing strength than to build a new one from scratch, with few exceptions. We also know that people-based supports are hard, and depend on significant coordination among universities, government agencies, and local employers for defining skills and constructing training programs accordingly. Even so, the policy world still has no silver bullet for ramping up the quantity and quality of STEM education—even as S&T jobs continue to grow. Finally, we know that place-based supports generally exist in innovative regions. But we do not have unambiguous causal evidence for the results of place-based supports in the absence of people-based supports. In other words, building physical infrastructure and amenities for the creative class is not enough to generate a robust S&T labor market.

Places and people through the lens of specialization and clustering

This dissertation provides a new lens for analyzing industry supports, other people-based supports, and place-based supports.

Disaggregating specialization and clustering changes industry supports by providing a finer lens to analyze industry structure within a region. For example, a regional policymaker considering an industry support for an industry that is low in both specialization and clustering for that region might proceed with caution; the literature suggests that creating a new industry specialization from scratch is difficult, and doing so without a small cluster to start with may be even harder. On the other hand, if the target industry were high on clustering but low on specialization, it would be possible to build on a small but dense core of expertise—something that would not show up with a location quotient analysis alone. For target industries that are high in both clustering and specialization, policy strategies likely involve supporting already strong people and places—an opportunity to invest in an industry's self-defined networks and initiatives. Finally, for target industries that are high in specialization but low in clustering, policymakers can ask themselves whether the existing spatial arrangement is meeting regional needs for S&T innovation and labor market reproduction. If the answer is yes, then policy strategies likely involve supporting existing networks; if the answer is no, then policy strategies likely involve a long-term plan to encourage more clustering.

In terms of other people-based supports, disaggregating specialization and clustering allows policymakers to distinguish between skill upgrading for the metropolitan area as a whole and skill upgrading in particular neighborhoods. Regional policy is hard partly because the region is not a political jurisdiction. While we have metropolitan statistical areas to define labor markets and serve as a Census unit of analysis, we do not have many models for the many municipalities and counties of a region to coordinate with one another. Especially when it comes to S&T labor markets, we are just as likely to see cities within the same region competing with one another for particular firms as we are to see them cooperating for the economic viability of the entire region. As the economic impact evaluation of the central Market Street payroll tax exclusion in San Francisco noted, the absence of the payroll tax exclusion likely would not have changed the labor market of the San Francisco MSA—but it did change the labor market of central Market Street. That is clustering in action, and it raises key questions about who shapes labor market outcomes at what scale.

And that brings us to place-based supports. Disaggregating specialization and clustering shows that clustering drives the wage premium we see in agglomerations—as far as we know from this dissertation. Future research should replicate this analysis with other S&T industries to confirm. In the meantime, it is possible that place-based supports, which encourage more dense company locations compared to people-based supports, may offer a higher return on policy investment. If the goal is to strengthen S&T labor markets—whether we measure this by the number of S&T jobs, the quality of those jobs, the level of innovation produced by those workers, or something else—it is possible that investing in getting a target industry into a particular neighborhood may help.

That said, this project provides but a beginning. To know what really works in strengthening S&T labor markets, several open questions need to be answered. Here are a few key avenues for future work.

First, future work should examine S&T labor market outcomes more directly. This study was limited to examining one outcome, wages, and one process, the method by which people found their current jobs. On the ground, policymakers assess the health of S&T labor markets using a variety of metrics, from the number and types of S&T jobs to the production and retention of S&T

graduates to S&T company and industry growth to S&T innovation indicators such as patents and awards. Examining whether specialization and clustering help predict these outcomes—alongside predictors we already know of from current literature—would go a long way in solidifying policy recommendations.

Second, future work should take into account other institutions known to be associated with innovative regions. For example, it would be interesting to find out whether a weighted clustering index that measures density based on proximity not only to other firms but to universities and other anchor institutions performs better in predicting S&T labor market outcomes. It is clear that firms, universities, and governments—along with organizations that connect and span those actors—all play a role in creating and sustaining S&T labor markets. Measuring the spatial proximity of those ties will extend this work and help policymakers choose sites for place-based investments.

Third, future work should take into account social network structures of different regions. Do specialization and clustering lead to structurally distinct social networks among S&T workers and firms? I would imagine that they do, if only due to the broad set of literature showing that physical proximity leads to more frequent social interaction. The effect drops precipitously as distance increases; I would thus expect social networks to include more strong ties in which everyone knows everyone in high clustering, low specialization regions compared to low clustering, low specialization regions. And as we know from the social network literature, strong ties are important for building trust and getting things done, while weak ties are important for finding new information and creating new things. Both are necessary for individual career success, and both are necessary in the aggregate for strong regional labor markets. The social network avenue also offers a way to measure physical proximity and frequency of interactions in different regions—a quantitative window into the anecdotes that say “everyone knows everyone and we bump into each other all the time” in a technology cluster.

Specialization and clustering change the game. By distinguishing between these two aspects of agglomeration, I provide a finer lens to analyze industry structure. That lens helps policymakers choose which kinds of industry supports to use in their work—if any. Further, I provide evidence that wage premiums in S&T agglomerations are hyperlocal. That finding provides a real argument for focusing on place-based supports, and it provides an opportunity for policymakers to prototype policy changes one city block or neighborhood at a time.

What remains to be seen is how changing models for S&T skill development and new federal investments in advanced manufacturing will shape the future of innovation in science and technology industries. For example, technology boot camps may provide a lasting service as a new form of labor market intermediary, or they may fade with the next technology bust. Similarly, initiatives like the National Network for Manufacturing Innovation (NNMI)[59] may create long-lasting physical and social infrastructure for S&T

[59] More details via the Advanced Manufacturing Portal: http://manufacturing.gov/nnmi.html.

innovation, or they may fade as one more experiment in seeding federally funded research centers.

In any case, mapping out the components of regional S&T labor markets is a long-term project. The components themselves change over time, as do the relationships between them. And while spatial proximity may be more important than social proximity in the short term—at least insofar as spatial proximity leads to social proximity—only time and replications of this work with other S&T industries will tell.

One of the most interesting experiments in S&T labor markets, particularly relevant to this dissertation, is the Integrated Photonics Institute for Manufacturing Innovation (IP-IMI).[60] Announced October 3, 2014, the White House press release states describes the IP-IMI as follows:[61]

> The Department of Defense is launching a competition to award more than $100 million in federal investment matched by $100 million or more in private investment to the winning consortia to build a new Institute for Manufacturing Innovation (IMI) focused on Integrated Photonics. This Institute will focus on developing an end-to-end photonics 'ecosystem' in the U.S., including domestic foundry access, integrated design tools, automated packaging, assembly and test, and workforce development.
>
> Each manufacturing innovation institute serves as a regional hub, bridging the gap between applied research and product development by bringing together companies, universities and other academic and training institutions, and Federal agencies to co-invest in key technology areas that encourage

[60] More details via the Advanced Manufacturing Portal: http://manufacturing.gov/ip-imi.html.

[61] White House Office of the Press Secretary, October 3, 2014. "FACT SHEET: President Obama Announces New Manufacturing Innovation Institute Competition." http://www.whitehouse.gov/the-press-office/2014/10/03/fact-sheet-president-obama-announces-new-manufacturing-innovation-instit

> investment and production in the U.S. This type of "teaching factory" provides a unique opportunity for education and training of students and workers at all levels, while providing the shared assets to help companies, most importantly small manufacturers, access the cutting-edge capabilities and equipment to design, test, and pilot new products and manufacturing processes.

The Air Force Research Laboratory released the official opportunity announcement on November 5, 2014.[62] Less than two weeks later, 191 representatives from industry, academia, and government[63] attended Proposers' Day, a series of meetings in Virginia "to familiarize potential proposers with the concept and vision for the Integrated Photonics Institute and the associated technology needs."[64] As of this writing, the structure and location of the eventual Integrated Photonics Institute is still unknown. Interested parties submitted concept papers on December 19, 2014; requests for full proposals will be sent to teams with the best concept papers.

For the purposes of this dissertation, the IP-IMI is interesting in three key ways. First, it shows that the photonics industry is a national priority. The Department of Defense has allocated $100 million for the Institute, and that will be matched by another $100 million from the private sector. Second, it shows that regions are actively competing to take part in the photonics industry. The funding is for an Institute to serve as a hub for a regional ecosystem of integrated photonics—which requires cooperation from universities, government agencies, and private sector firms. Consortia of these

[62] Record on FedBizOpps.gov: https://www.fbo.gov/index?s=opportunity&mode=form&id=a354f1a61c1e7f0a5f222ae309b5ae8e

[63] Full list of attendees available at http://manufacturing.gov/docs/ip-imi-ProposersDay-attendees.pdf.

[64] Quote from IP-IMI home page at http://manufacturing.gov/ip-imi.html.

actors from different regions are submitting proposals to procure funding for the Institute. Third, the IP-IMI provides an example of an integrated approach to research, product development, and skills training. Proposals for the Institute are evaluated not only on their business plans but also on technical, education, and workforce development criteria, such as building on existing STEM activities to develop photonics-specific curricula for K-12, community colleges, and four-year universities. It will be interesting to see how the IP-IMI changes not only the S&T labor market in which it ends up locating, but also the landscape of photonics labor markets in the United States as a whole. And policymakers in regions across the country will look to the IP-IMI for evaluation lessons on what strategies work for creating integrated S&T ecosystems at the regional scale.

Policy recommendations

The policy recommendations from this dissertation are necessarily tentative. Future research is needed to overcome the theoretical and empirical limitations in this work. That said, given the evidence in this dissertation, and given the broader research literature on S&T agglomerations, it is possible to make two key policy recommendations.

The first is that regional economic developers would do well to consider where their target industries fall in terms of specialization and clustering. The strategies to encourage industries vary based on the quadrant in which they fall. Low specialization, low clustering industries are unlikely to become regional differentiators, and may not be worth public investment. Low specialization, high clustering industries have the potential for building expertise in a niche area that would not show up in a traditional location quotient analysis. Those industries can be encouraged to prototype new products and services with small funds for rapid experiments. High clustering, high specialization industries are the darlings of economic development; in this case, economic developers would do well to ask the key actors in the industry what they need to grow, and then listen and do what they can. In other words, this is an opportunity to invest in an industry that is already locally strong and likely full of self-defined networks and initiatives. High specialization, low clustering industries could use one of two types of intervention. If these industries are already meeting regional needs for S&T innovation and labor market reproduction—in other words, if they are creating enough new products and services and hiring and training enough local workers—then economic developers would do well to support existing networks, similar to the strategy for high specialization, high clustering regions. If, however, these industries are not meeting both of those needs—they fall short on S&T innovation, labor market reproduction, or both—then economic developers may consider long-term plans to encourage clustering through mechanisms such as geographically bounded payroll tax exemptions. Such plans are not a substitute for encouraging social networks and knowledge transfer; rather, they are a way to complement those strategies with the added nudge of physical proximity.

The second policy recommendation is to experiment with place-based approaches to strengthening S&T labor markets. While I do not advocate an abandonment of people-based approaches, particularly in the realm of skill development, adding place-based approaches to the mix might be helpful. For example, experimenting with a payroll tax exclusion for a particular industry in an already strong S&T labor market areas—provided that comprehensive policy evaluations are built into the plan—could yield useful insights about which labor market indicators are most helped by place-based approaches. Such insights could then be used to prioritize public spending in the future. If a payroll tax exclusion feels like too much of a risk or too high of a cost, economic developers could experiment with preferential zoning—or even fast-tracked zoning applications—for certain kinds of S&T firms in already strong S&T labor market areas.

Policy decisions should be tailored to regional conditions. These conditions include regional specialization and clustering as well as labor market characteristics such as role-specific supply and demand. Policymakers can choose among tools to influence labor supply, labor demand, or connections between supply and demand. Policy tools to influence labor supply generally fall into the category of people-based supports for labor market upskilling and reproduction. Policy tools to influence labor demand generally fall into the category of place-based supports for firm expansion, though they can also include people-based supports for particular employers or industries regardless of geography. Policy tools to influence the connections between labor supply and demand include creating or supporting labor market intermediaries and investing in research and development.

Selecting the right policy tool for the job requires a clear articulation of policy goals and regional conditions. For example, if the policy goal is to develop a regional data science hub, then the next step is to assess regional conditions in relation to this goal. To what degree is the region already specialized and clustered in data science? If the region already exhibits specialization in data science, and if firms in the industry agree that they are producing enough product and process innovations and have no trouble meeting their hiring goals for data scientists, then policymakers should consider emphasizing place-based supports to help firms expand. For example, policymakers could use payroll tax exclusions in a specific neighborhood to encourage firms to hire more rapidly and to collaborate with one another more. The effects of the payroll tax exclusions would likely be larger if firms in the region are not already clustered. If firms in the region are already clustered, policymakers should also consider upgrading infrastructure that connects firms with universities and other data scientists both within and outside the region, as both regional and non-regional ties accelerate growth.

On the other hand, if the region does not exhibit specialization in data science, or if firms in the industry are dissatisfied with their rate of product and process innovation, or if firms in the industry have trouble finding skilled labor for data science roles, then people-based supports are in order. In this case, policy interventions should focus on upskilling and labor market reproduction for data science: provide financial incentives for providers of data science education to increase their offers, or for universities, boot camps, and the like to create offerings where there are none. Such interventions may include the strategic hiring of faculty and technical leads from other cities with larger data science hubs. S&T firms cannot expand without access to an adequate supply of technical talent, so producing that talent through regional universities and vocational training programs is the policy priority.

APPENDIX A: PYTHON SCRIPT FOR *PHOTONICS BUYERS' GUIDE* SCRAPING

```
# file name: get-firm-data.py

from bs4 import BeautifulSoup
import sys
import codecs

# open file, convert to string, give to BeautifulSoup
filename = sys.argv[1]
input_file = open(filename,'rb')
page = input_file.read()
input_file.close()
soup = BeautifulSoup(page)
# print "Soup Object: ", soup

# extract company ID from filename
companyID = filename.split("=")[-1]
print "Company ID: ", companyID

# extract company name
companyName = soup.findAll(attrs={"class":"BG_Breadcrumb"})[0].b.string
print "Company Name: ", companyName

# extract company website

try:
	companyWebsiteBlock =
soup.findAll(attrs={"id":"ctl00_BodyContent_PAN_WebInfo"})[0]
	companyURL = companyWebsiteBlock.findAll('a')[-1].get('href').split("=")[-
1]
except Exception:
	companyURL = ""
print "Company URL: ", companyURL

# extract address
addressBlock = soup.findAll(attrs={"id":"ctl00_BodyContent_PAN_Address"})
# print "Address Block: ", addressBlock

# extract street
companyStreet = addressBlock[0].b

print "Street: ", companyStreet

addressList = []

for string in companyStreet.strings:
    addressList.append(str(string))

print "Address List: ", addressList, len(addressList)

companyStreet = addressList[0]

# if len(addressList) == 3:
#	companyCityStateZip = addressList[1]
# elif len(addressList) > 3:
#	companyCityStateZip = addressList[2]
# else:
#	companyCityStateZip = addressList[-2]
```

```
#       raise Exception("Weird Company Address: "+ companyID)

for i,field in enumerate(addressList):
        if "United States" in field:
                companyCityStateZip = addressList[i-1]


csz = companyCityStateZip.split(',')
companyCity    = csz[0]

sz = csz[1].split()
companyState = sz[0]
companyZip = sz[1][:5]


print "Company Street: ", companyStreet
print "Company City: ", companyCity
print "Company State: ", companyState
print "Company Zip: ", companyZip

# extract street 2
# extract city
# extract state
# extract zip
# extract Google Maps URL

try:
        gMapsURL = addressBlock[0].b.a.get('href')
except Exception:
        gMapsURL = ""
print "Google Maps URL: ", gMapsURL

# description
try:
        companyDescription =
unicode.encode(soup.findAll(attrs={"id":"ctl00_BodyContent_PAN_Description"})[0].c
ontents[0].strip().replace('\n',' '))
except:
        companyDescription = ""

# print "Description: ", companyDescription

# stats: established, employees, square footage
# which stats are available?
try:
        companyStats =
soup.findAll(attrs={"id":"ctl00_BodyContent_PAN_Demographics"})[0].contents
except Exception:
        companyStats = []

companyEstablished = ""
companyEmployees = ""
companySqFt = ""

for i in xrange(0,len(companyStats)):
        if "Established" in str(companyStats[i]):
                companyEstablished = str(companyStats[i+1]).strip()
        if "Employees" in str(companyStats[i]):
                companyEmployees = str(companyStats[i+1]).strip()
        if "Facility" in str(companyStats[i]):
                companySqFt = int(str(companyStats[i+1]).strip().replace(',',''))

print "Established: ", companyEstablished
print "Employees: ", companyEmployees
print "Facility Square Footage: ", companySqFt

record = [
companyID,
companyName,
companyStreet,
companyCity,
companyState,
```

```
companyZip,
gMapsURL,
companyDescription,
companyEstablished,
companyEmployees,
companySqFt,
companyURL]

import csv

#with open(companyID+".csv",'wb') as outfile:
csvwriter = csv.writer(sys.stdout,delimiter = ',',quoting = csv.QUOTE_ALL)
csvwriter.writerow(record)
```

APPENDIX B: PYTHON SCRIPT FOR CALCULATING AVERAGE NEAREST NEIGHBOR DISTANCE

```
#!/usr/bin/env python

# file name: nearestneighbors.py
# thank you to the ArcGIS forum user setanrabb for the script template
# http://forums.arcgis.com/threads/45487-Average-Nearest-Neighbour-results-
table?highlight=AverageNearestNeighbors

# import libraries

import arcinfo, arcpy, glob, os, string, sys, arcgisscripting, math
from arcpy import env, mapping, conversion, sa
gp = arcgisscripting.create()
gp.overwriteoutput = True

# Set the workspace and list feature classes
env.workspace = "C:\Users\Kirsten\Data\ArcGIS\PBG by CBSA\SBA
PBG_Geocoded_Project\SBA.gdb"
fcs = arcpy.ListFeatureClasses()

# Create a dictionary
nn = {}

# For each feature class in the list of feature classes
for fc in fcs:
    try:
        nn[fc] = gp.AverageNearestNeighbor_stats(fc, "EUCLIDEAN_DISTANCE",
"GENERATE_REPORT")
    except Exception:
        pass


# Make output table
with open(r"C:\Users\Kirsten\Data\ArcGIS\results.csv","w") as resfile:
    print >> resfile, "cbsa_code, nn_index, nn_zscore, nn_pvalue, nn_emean,
nn_omean, nn_report"

    for fc in nn:
        nn_output = nn[fc]
        nn_values = nn_output.split(";")
        print >> resfile,fc.split('_')[-1:][0] + ", " + ",".join([str(d) for d in
nn_values])

####

try:
    # Set the current workspace (to avoid having to specify the full path to the
feature classes each time)
    arcpy.env.workspace = workspace

    # Obtain Nearest Neighbor Ratio and z-score
    # Process: Average Nearest Neighbor...
    nn_output = gp.AverageNearestNeighbor_stats(crime_data, "EUCLIDEAN_DISTANCE",
"NO_REPORT", "#")
```

```
    # Create list of Average Nearest Neighbor output values by splitting the
result object
    nn_values = nn_output.split(";")
    print "The nearest neighbor index is: " + nn_values[0]
    print "The z-score of the nearest neighbor index is: " + nn_values[1]
    print "The p-value of the nearest neighbor index is: " + nn_values[2]
    print "The expected mean distance is: " + nn_values[3]
    print "The observed mean distance is: " + nn_values[4]
    print "The path of the HTML report: " + nn_values[5]

# View output
for fc in nn:
    nn_output = nn[fc]
    nn_values = nn_output.split(";")
    print "The nearest neighbor index is: " + nn_values[0]
    print "The z-score of the nearest neighbor index is: " + nn_values[1]
    print "The p-value of the nearest neighbor index is: " + nn_values[2]
    print "The expected mean distance is: " + nn_values[3]
    print "The observed mean distance is: " + nn_values[4]
    print "The path of the HTML report: " + nn_values[5]


        '''
    print "The nearest neighbor index is: " + nn_values[0]
    print "The z-score of the nearest neighbor index is: " + nn_values[1]
    print "The p-value of the nearest neighbor index is: " + nn_values[2]
    print "The expected mean distance is: " + nn_values[3]
    print "The observed mean distance is: " + nn_values[4]
    print "The path of the HTML report: " + nn_values[5]
    '''
```

APPENDIX C: R SCRIPT FOR CALCULATING REGIONAL SPECIALIZATION

```
# Filename: lq_stat.R

# aggregate pbg2012 by msa to get firm counts
attach(pbg2012)
msa_firm_counts <- as.data.frame(table(msa))
colnames(msa_firm_counts) <- c("msa", "pbg_f")
detach(pbg2012)

# join w/ county business patterns to get establishment counts
  # drop micropolitan areas from CBP data
  census10_cbsa_data$msa <- census10_cbsa_data$GEOID10
  CBP_Census <- merge(cbp10msa_agg, census10_cbsa_data, by="msa")
  CBP_Census_metro <- CBP_Census[which(CBP_Census$MEMI10==1),]

  # join w/ PBG
  CBP_Census_PBG_Metro <- merge(CBP_Census_metro, msa_firm_counts, by="msa",
all.x= TRUE)

# calculate SLQ
SLQ_calc <- CBP_Census_PBG_Metro # rename for ease of typing


attach(SLQ_calc)
SLQ_calc$pct_photonics <- pbg_f / est
SLQ_calc$msa_lq <- SLQ_calc$pct_photonics / pct_photonics_us
SLQ_calc$log_lq <- log(SLQ_calc$msa_lq)
detach(SLQ_calc)

# normality test of LQs: Shapiro-Wilk test
shapiro.test(SLQ_calc$msa_lq) # p < .05 not normal
shapiro.test(SLQ_calc$log_lq) # p = 0.3564 normal

# normality test of LQs: Kolmogorov-Smirnov test
ks.test(SLQ_calc$msa_lq, "pnorm") # p < .05 not normal
ks.test(SLQ_calc$log_lq, "pnorm") # p = .06 normal?

# Q-Q plots
qqnorm(SLQ_calc$msa_lq) # clearly not normal
qqnorm(SLQ_calc$log_lq) # normal

# calculate z-scores
SLQ_calc$z_lq <- ( SLQ_calc$log_lq - mean(SLQ_calc$log_lq, na.rm=TRUE) ) /
sd(SLQ_calc$log_lq, na.rm=TRUE)

# view all the z-scores
sort(SLQ_calc$z_lq)
```

APPENDIX D: LQ, LOG(LQ), AND SLQ FOR 186 REGIONS

Table 29. LQ, log(LQ), and SLQ for 186 regions.

MSA ID	MSA NAME	LQ	LOG(LQ)	SLQ
10420	Akron, OH	0.91	-0.09	0.02
10580	Albany-Schenectady-Troy, NY	1.08	0.08	0.20
10740	Albuquerque, NM	2.02	0.71	0.88
10900	Allentown-Bethlehem-Easton, PA-NJ	2.76	1.01	1.22
11100	Amarillo, TX	0.42	-0.87	-0.82
11180	Ames, IA	2.48	0.91	1.10
11340	Anderson, SC	1.37	0.32	0.46
11460	Ann Arbor, MI	7.02	1.95	2.23
12020	Athens-Clarke County, GA	0.57	-0.55	-0.48
12060	Atlanta-Sandy Springs-Marietta, GA	0.55	-0.60	-0.54
12260	Augusta-Richmond County, GA-SC	0.24	-1.41	-1.41
12420	Austin-Round Rock-San Marcos, TX	0.73	-0.31	-0.22
12580	Baltimore-Towson, MD	1.08	0.08	0.20
12700	Barnstable Town, MA	0.31	-1.18	-1.16
13140	Beaumont-Port Arthur, TX	0.32	-1.14	-1.12
13380	Bellingham, WA	0.40	-0.91	-0.87
13460	Bend, OR	1.74	0.55	0.72
13780	Binghamton, NY	1.48	0.39	0.54
13980	Blacksburg-Christiansburg-Radford, VA	1.54	0.43	0.59
14020	Bloomington, IN	1.30	0.26	0.40
14260	Boise City-Nampa, ID	0.31	-1.18	-1.16
14460	Boston-Cambridge-Quincy, MA-NH	5.00	1.61	1.86
14500	Boulder, CO	6.83	1.92	2.20
14740	Bremerton-Silverdale, WA	0.89	-0.11	-0.01
14860	Bridgeport-Stamford-Norwalk, CT	3.36	1.21	1.43
15380	Buffalo-Niagara Falls, NY	1.50	0.41	0.56
15540	Burlington-South Burlington, VT	3.00	1.10	1.31

MSA ID	MSA NAME	LQ	LOG(LQ)	SLQ
15980	Cape Coral-Fort Myers, FL	0.16	-1.82	-1.86
16180	Carson City, NV	1.18	0.16	0.30
16580	Champaign-Urbana, IL	1.03	0.03	0.15
16700	Charleston-North Charleston-Summerville, SC	0.15	-1.87	-1.91
16620	Charleston, WV	0.69	-0.37	-0.29
16740	Charlotte-Gastonia-Rock Hill, NC-SC	0.57	-0.57	-0.50
16860	Chattanooga, TN-GA	0.45	-0.79	-0.74
16940	Cheyenne, WY	1.87	0.62	0.79
16980	Chicago-Joliet-Naperville, IL-IN-WI	1.08	0.07	0.20
17020	Chico, CA	0.54	-0.62	-0.56
17140	Cincinnati-Middletown, OH-KY-IN	0.49	-0.71	-0.65
17300	Clarksville, TN-KY	0.59	-0.53	-0.46
17460	Cleveland-Elyria-Mentor, OH	1.11	0.11	0.23
17820	Colorado Springs, CO	0.61	-0.49	-0.42
17980	Columbus, GA-AL	0.44	-0.82	-0.77
18140	Columbus, OH	0.77	-0.26	-0.17
18700	Corvallis, OR	2.45	0.90	1.09
19060	Cumberland, MD-WV	1.18	0.16	0.30
19100	Dallas-Fort Worth-Arlington, TX	0.74	-0.31	-0.21
19260	Danville, VA	1.13	0.12	0.25
19380	Dayton, OH	2.32	0.84	1.03
19660	Deltona-Daytona Beach-Ormond Beach, FL	0.64	-0.44	-0.36
19740	Denver-Aurora-Broomfield, CO	0.68	-0.38	-0.29
19780	Des Moines-West Des Moines, IA	0.17	-1.77	-1.81
19820	Detroit-Warren-Livonia, MI	0.88	-0.13	-0.02
20500	Durham-Chapel Hill, NC	0.65	-0.43	-0.35
21340	El Paso, TX	0.38	-0.97	-0.94
21140	Elkhart-Goshen, IN	0.52	-0.66	-0.60
21300	Elmira, NY	2.72	1.00	1.20
21500	Erie, PA	0.40	-0.91	-0.87
21660	Eugene-Springfield, OR	1.58	0.46	0.61
22020	Fargo, ND-MN	0.40	-0.91	-0.87
22500	Florence, SC	0.59	-0.54	-0.46
22660	Fort Collins-Loveland, CO	1.08	0.07	0.20
23060	Fort Wayne, IN	1.21	0.19	0.32
23540	Gainesville, FL	0.84	-0.17	-0.07
24300	Grand Junction, CO	1.63	0.49	0.65
24340	Grand Rapids-Wyoming, MI	0.28	-1.27	-1.26
24540	Greeley, CO	2.44	0.89	1.09
24580	Green Bay, WI	0.33	-1.11	-1.08

MSA ID	MSA NAME	LQ	LOG(LQ)	SLQ
24660	Greensboro-High Point, NC	0.14	-1.94	-1.99
24860	Greenville-Mauldin-Easley, SC	1.01	0.01	0.12
25420	Harrisburg-Carlisle, PA	0.94	-0.06	0.05
25540	Hartford-West Hartford-East Hartford, CT	3.33	1.20	1.42
25860	Hickory-Lenoir-Morganton, NC	0.33	-1.11	-1.08
26100	Holland-Grand Haven, MI	0.89	-0.12	-0.01
26180	Honolulu, HI	0.12	-2.15	-2.21
26420	Houston-Sugar Land-Baytown, TX	0.23	-1.49	-1.49
26620	Huntsville, AL	1.08	0.08	0.20
26820	Idaho Falls, ID	0.69	-0.37	-0.28
26900	Indianapolis-Carmel, IN	0.66	-0.42	-0.34
27060	Ithaca, NY	5.44	1.69	1.95
27260	Jacksonville, FL	0.22	-1.50	-1.51
28020	Kalamazoo-Portage, MI	0.73	-0.32	-0.23
28140	Kansas City, MO-KS	0.40	-0.91	-0.87
28700	Kingsport-Bristol-Bristol, TN-VA	0.41	-0.88	-0.84
28740	Kingston, NY	0.54	-0.62	-0.56
28940	Knoxville, TN	0.79	-0.24	-0.14
29140	Lafayette, IN	0.64	-0.45	-0.37
29420	Lake Havasu City-Kingman, AZ	0.68	-0.39	-0.30
29540	Lancaster, PA	0.21	-1.56	-1.58
29620	Lansing-East Lansing, MI	0.53	-0.64	-0.58
29820	Las Vegas-Paradise, NV	0.38	-0.96	-0.93
30700	Lincoln, NE	0.92	-0.08	0.03
30780	Little Rock-North Little Rock-Conway, AR	0.72	-0.33	-0.24
30860	Logan, UT-ID	2.26	0.81	1.00
31020	Longview, WA	1.14	0.13	0.26
31100	Los Angeles-Long Beach-Santa Ana, CA	1.69	0.53	0.69
31140	Louisville/Jefferson County, KY-IN	0.17	-1.78	-1.81
31540	Madison, WI	1.50	0.41	0.56
31700	Manchester-Nashua, NH	9.09	2.21	2.51
31900	Mansfield, OH	0.92	-0.08	0.03
32780	Medford, OR	0.44	-0.83	-0.78
33100	Miami-Fort Lauderdale-Pompano Beach, FL	0.31	-1.17	-1.15
33140	Michigan City-La Porte, IN	2.04	0.71	0.89
33340	Milwaukee-Waukesha-West Allis, WI	0.79	-0.24	-0.14
33460	Minneapolis-St. Paul-Bloomington, MN-WI	1.04	0.04	0.16
34740	Muskegon-Norton Shores, MI	1.49	0.40	0.55
34900	Napa, CA	0.64	-0.45	-0.37
34980	Nashville-Davidson--Murfreesboro--Franklin, TN	0.34	-1.09	-1.07

MSA ID	MSA NAME	LQ	LOG(LQ)	SLQ
35300	New Haven-Milford, CT	1.80	0.59	0.76
35380	New Orleans-Metairie-Kenner, LA	0.09	-2.45	-2.53
35620	New York-Northern New Jersey-Long Island, NY-NJ-PA	1.23	0.21	0.34
35660	Niles-Benton Harbor, MI	0.69	-0.38	-0.29
35980	Norwich-New London, CT	1.31	0.27	0.41
36260	Ogden-Clearfield, UT	0.67	-0.41	-0.32
36740	Orlando-Kissimmee-Sanford, FL	1.51	0.41	0.57
36780	Oshkosh-Neenah, WI	0.70	-0.36	-0.27
37100	Oxnard-Thousand Oaks-Ventura, CA	4.63	1.53	1.78
37340	Palm Bay-Melbourne-Titusville, FL	1.75	0.56	0.72
37460	Panama City-Lynn Haven-Panama City Beach, FL	0.56	-0.57	-0.51
37620	Parkersburg-Marietta-Vienna, WV-OH	0.67	-0.40	-0.32
37700	Pascagoula, MS	1.94	0.66	0.83
37860	Pensacola-Ferry Pass-Brent, FL	0.28	-1.28	-1.27
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1.67	0.51	0.68
38060	Phoenix-Mesa-Glendale, AZ	0.78	-0.25	-0.16
38300	Pittsburgh, PA	1.58	0.45	0.61
38340	Pittsfield, MA	3.13	1.14	1.35
38940	Port St. Lucie, FL	1.02	0.02	0.14
38860	Portland-South Portland-Biddeford, ME	0.58	-0.54	-0.47
38900	Portland-Vancouver-Hillsboro, OR-WA	1.53	0.43	0.58
39100	Poughkeepsie-Newburgh-Middletown, NY	1.36	0.31	0.45
39300	Providence-New Bedford-Fall River, RI-MA	1.96	0.67	0.85
39340	Provo-Orem, UT	0.70	-0.36	-0.27
39460	Punta Gorda, FL	0.72	-0.33	-0.25
39580	Raleigh-Cary, NC	0.44	-0.83	-0.78
39740	Reading, PA	1.83	0.60	0.77
39820	Redding, CA	2.33	0.85	1.04
39900	Reno-Sparks, NV	0.86	-0.16	-0.05
40140	Riverside-San Bernardino-Ontario, CA	1.09	0.08	0.21
40220	Roanoke, VA	0.31	-1.18	-1.16
40380	Rochester, NY	9.54	2.26	2.56
40420	Rockford, IL	0.34	-1.09	-1.07
40900	Sacramento--Arden-Arcade--Roseville, CA	0.91	-0.10	0.01
41420	Salem, OR	0.28	-1.27	-1.26
41500	Salinas, CA	0.30	-1.20	-1.18
41620	Salt Lake City, UT	0.48	-0.73	-0.68
41700	San Antonio-New Braunfels, TX	0.13	-2.08	-2.14
41740	San Diego-Carlsbad-San Marcos, CA	2.43	0.89	1.08
41860	San Francisco-Oakland-Fremont, CA	1.97	0.68	0.85
41940	San Jose-Sunnyvale-Santa Clara, CA	8.40	2.13	2.43

MSA ID	MSA NAME	LQ	LOG(LQ)	SLQ
42020	San Luis Obispo-Paso Robles, CA	1.62	0.48	0.64
42060	Santa Barbara-Santa Maria-Goleta, CA	5.85	1.77	2.03
42100	Santa Cruz-Watsonville, CA	3.72	1.31	1.54
42140	Santa Fe, NM	2.64	0.97	1.17
42220	Santa Rosa-Petaluma, CA	3.25	1.18	1.40
42340	Savannah, GA	0.30	-1.20	-1.18
42540	Scranton--Wilkes-Barre, PA	0.38	-0.97	-0.94
42660	Seattle-Tacoma-Bellevue, WA	0.76	-0.28	-0.19
43100	Sheboygan, WI	0.94	-0.06	0.05
43300	Sherman-Denison, TX	1.00	0.00	0.12
43780	South Bend-Mishawaka, IN-MI	0.75	-0.29	-0.19
43900	Spartanburg, SC	1.59	0.47	0.62
44060	Spokane, WA	1.02	0.02	0.14
44140	Springfield, MA	2.55	0.94	1.13
41180	St. Louis, MO-IL	0.50	-0.69	-0.63
44300	State College, PA	1.58	0.46	0.61
44700	Stockton, CA	0.47	-0.76	-0.71
45060	Syracuse, NY	1.49	0.40	0.55
45220	Tallahassee, FL	0.29	-1.24	-1.22
45300	Tampa-St. Petersburg-Clearwater, FL	0.87	-0.14	-0.03
45460	Terre Haute, IN	1.35	0.30	0.44
45780	Toledo, OH	0.69	-0.37	-0.29
45940	Trenton-Ewing, NJ	5.43	1.69	1.95
46060	Tucson, AZ	5.34	1.67	1.93
46140	Tulsa, OK	0.31	-1.16	-1.14
46540	Utica-Rome, NY	3.74	1.32	1.55
47220	Vineland-Millville-Bridgeton, NJ	4.25	1.45	1.69
47260	Virginia Beach-Norfolk-Newport News, VA-NC	0.54	-0.62	-0.56
47300	Visalia-Porterville, CA	0.82	-0.20	-0.09
47380	Waco, TX	0.51	-0.67	-0.61
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	0.47	-0.77	-0.71
47940	Waterloo-Cedar Falls, IA	0.61	-0.49	-0.42
48620	Wichita, KS	0.17	-1.76	-1.80
48900	Wilmington, NC	0.77	-0.27	-0.17
49180	Winston-Salem, NC	0.49	-0.72	-0.66
49340	Worcester, MA	5.30	1.67	1.92
49620	York-Hanover, PA	0.59	-0.53	-0.46
49740	Yuma, AZ	0.86	-0.16	-0.05

APPENDIX E: 2012 SPIE SALARY SURVEY

2012 SPIE Global Salary Survey

Question Text

Thank you for participating in the annual SPIE Global Salary Survey. All participants are eligible to receive a preliminary report on survey results and to be entered into a drawing for an iPad2.

Survey results will be analyzed on an aggregate basis. All identifying information remains strictly confidential.

This survey should take about 5 to 10 minutes to complete. Thank you for participating.

The SPIE Team

What is your current employment status? (select one)

- ❍ Full-time employed
- ❍ Part-time employed (30 hours or less per work week)
- ❍ Unemployed
- ❍ Retired >>>> Skip to Page 16: Do you have any other thoughts that you would like to share with the SPIE staff? (Optional)

(End of Page 1)

Text
In what country are you employed or were you most recently employed?

- ❍ Afghanistan
- ❍ Albania
- ❍ Algeria
- ❍ Andorra
- ❍ Angola
- ❍ Antigua and Barbuda
- ❍ Argentina
- ❍ Armenia
- ❍ Australia
- ❍ Austria
- ❍ Azerbaijan
- ❍ Bahamas
- ❍ Bahrain
- ❍ Bangladesh
- ❍ Barbados
- ❍ Belarus
- ❍ Belgium
- ❍ Belize
- ❍ Benin
- ❍ Bhutan
- ❍ Bolivia
- ❍ Bosnia
- ❍ Botswana
- ❍ Brazil
- ❍ Brunei Darussalam
- ❍ Bulgaria
- ❍ Burkina Faso
- ❍ Burundi
- ❍ Cambodia
- ❍ Cameroon
- ❍ Canada
- ❍ Cape Verde
- ❍ Central African Republic
- ❍ Chad
- ❍ Chile
- ❍ China, People's Republic of
- ❍ Colombia
- ❍ Comoros
- ❍ Congo, Democratic Republic of the
- ❍ Congo, Republic of the
- ❍ Costa Rica
- ❍ Cote d'Ivoire
- ❍ Croatia
- ❍ Cuba
- ❍ Cyprus
- ❍ Czech Republic
- ❍ Denmark
- ❍ Djibouti
- ❍ Dominica
- ❍ Dominican Republic
- ❍ East Timor
- ❍ Ecuador
- ❍ Egypt
- ❍ El Salvador

❍ Equatorial Guinea
❍ Eritrea
❍ Estonia
❍ Ethiopia
❍ Fiji
❍ Finland
❍ France
❍ Gabon
❍ Gambia
❍ Georgia
❍ Germany
❍ Ghana
❍ Greece
❍ Grenada
❍ Guatemala
❍ Guinea
❍ Guinea-Bissau
❍ Guyana
❍ Haiti
❍ Honduras
❍ Hungary
❍ Iceland
❍ India
❍ Indonesia
❍ Iran
❍ Iraq
❍ Ireland
❍ Israel
❍ Italy
❍ Jamaica
❍ Japan
❍ Jordan
❍ Kazakhstan
❍ Kenya
❍ Kiribati
❍ Korea, North
❍ Korea, South
❍ Kosovo
❍ Kuwait
❍ Kyrgyzstan
❍ Laos
❍ Latvia
❍ Lebanon
❍ Lesotho
❍ Liberia
❍ Libya
❍ Liechtenstein
❍ Lithuania
❍ Luxembourg
❍ Macedonia
❍ Madagascar
❍ Malawi
❍ Malaysia
❍ Maldives
❍ Mali
❍ Malta

- Marshall Islands
- Mauritania
- Mauritius
- Mexico
- Micronesia
- Moldova
- Monaco
- Mongolia
- Montenegro
- Morocco
- Mozambique
- Myanmar
- Namibia
- Nauru
- Nepal
- Netherlands
- New Zealand
- Nicaragua
- Niger
- Nigeria
- Northern Ireland
- Norway
- Oman
- Pakistan
- Palau
- Palestine State
- Panama
- Papua New Guinea
- Paraguay
- Peru
- Philippines
- Poland
- Portugal
- Qatar
- Romania
- Russian Federation
- Rwanda
- Saint Kitts and Nevis
- Saint Lucia
- Saint Vincent and the Grenadines
- Samoa
- San Marino
- Sao Tome and Principe
- Saudi Arabia
- Senegal
- Serbia
- Seychelles
- Sierra Leone
- Singapore
- Slovakia
- Slovenia
- Solomon Islands
- Somalia
- South Africa
- Spain
- Sri Lanka

❍ Sudan
❍ Suriname
❍ Swaziland
❍ Sweden
❍ Switzerland
❍ Syria
❍ Taiwan
❍ Tajikistan
❍ Tanzania
❍ Thailand
❍ Togo
❍ Tonga
❍ Trinidad and Tobago
❍ Tunisia
❍ Turkey
❍ Turkmenistan
❍ Tuvalu
❍ Uganda
❍ Ukraine
❍ United Arab Emirates
❍ United Kingdom
❍ United States >>>> Skip to Page 3: In what state are you employed or were you most recently employed?
❍ Uruguay
❍ Uzbekistan
❍ Vanuatu
❍ Venezuela
❍ Vietnam
❍ Yemen
❍ Zambia
❍ Zimbabwe

(End of Page 2)

In what state are you employed or were you most recently employed?

- ❍ Alabama
- ❍ Alaska
- ❍ American Samoa
- ❍ Arizona
- ❍ Arkansas
- ❍ California
- ❍ Colorado
- ❍ Connecticut
- ❍ Delaware
- ❍ District of Columbia
- ❍ Florida
- ❍ Georgia
- ❍ Guam
- ❍ Hawaii
- ❍ Idaho
- ❍ Illinois
- ❍ Indiana
- ❍ Iowa
- ❍ Kansas
- ❍ Kentucky
- ❍ Louisiana
- ❍ Maine
- ❍ Maryland
- ❍ Massachusetts
- ❍ Michigan
- ❍ Minnesota
- ❍ Mississippi
- ❍ Missouri
- ❍ Montana
- ❍ Nebraska
- ❍ Nevada
- ❍ New Hampshire
- ❍ New Jersey
- ❍ New Mexico
- ❍ New York
- ❍ North Carolina
- ❍ North Dakota
- ❍ Northern Marianas Islands
- ❍ Ohio
- ❍ Oklahoma
- ❍ Oregon
- ❍ Pennsylvania
- ❍ Puerto Rico
- ❍ Rhode Island
- ❍ South Carolina
- ❍ South Dakota
- ❍ Tennessee
- ❍ Texas
- ❍ Utah
- ❍ Vermont
- ❍ Virginia
- ❍ Virgin Islands
- ❍ Washington
- ❍ West Virginia
- ❍ Wisconsin

❍ Wyoming

(End of Page 3)

Please enter the five-digit ZIP Code of your current or most recent workplace. This data is used for regional comparisons only. (optional) ____________________

(End of Page 4)

What is your role in your current or most recent job? (select one)
- ❍ Business Development
- ❍ Consultant
- ❍ Engineering & Design
- ❍ Investor/VC/Financier
- ❍ Leadership
- ❍ Librarian
- ❍ Marketing
- ❍ Press
- ❍ Production/Manufacturing
- ❍ Project/Program Management
- ❍ Purchasing
- ❍ Recruiting/HR/Training
- ❍ R&D: Application/Product Development
- ❍ R&D: Applied Research
- ❍ R&D: Basic Research/Science
- ❍ Sales
- ❍ Student
- ❍ Technical/Lab
- ❍ University/college professor
- ❍ Other ____________________________________

What is your current or most recent job level? (select one)
- ❍ Technician/Operator/Lab Tech
- ❍ Staff
- ❍ Lead/Senior level
- ❍ Supervisor/Manager
- ❍ Director
- ❍ V.P.
- ❍ C-level
- ❍ Graduate or undergraduate student
- ❍ Instructor or Adjunct Professor
- ❍ Assistant or Associate Professor
- ❍ Full Professor
- ❍ Academic Dean, Provost
- ❍ Other ____________________________________

What is your specific job title?
Job title ____________________

What is your gender? (select one)
- ❍ Female
- ❍ Male

(End of Page 5)

What is your organization or employer type? (select one)

- ❍ Company/corporation
- ❍ University/college
- ❍ Military/defense
- ❍ Civilian government
- ❍ Government laboratory or research institute
- ❍ Private laboratory or research institute
- ❍ Other research institute
- ❍ Not-for-profit organization
- ❍ Self-employed/consultant

How many employees are in your organization (world-wide)? (select one)

- ❍ Less than 10 employees
- ❍ 11-50 employees
- ❍ 51-100 employees
- ❍ 101-250 employees
- ❍ 251-1000 employees
- ❍ 1001-2500 employees
- ❍ 2501-5000 employees
- ❍ More than 5000 employees

(End of Page 6)

Select the primary discipline of your most recent work or teaching. If your work is primarily managerial, business development, or administrative, please select the primary focus or market of your division or organization. (select one)

- ❍ Aerospace
- ❍ Astronomy/astrophysics
- ❍ Biomedical/medical
- ❍ Civil/environmental
- ❍ Chemical
- ❍ Computer science/software/information technology
- ❍ Electrical
- ❍ Illumination
- ❍ Interdisciplinary engineering or research
- ❍ Lasers
- ❍ Manufacturing
- ❍ Materials
- ❍ Mechanical
- ❍ Nanotechnology
- ❍ Optical design
- ❍ Optical systems
- ❍ Photonics
- ❍ Physics
- ❍ Remote sensing
- ❍ Semiconductor
- ❍ Systems engineering or research
- ❍ Other ____________________

(End of Page 7)

What is the highest educational level you have completed? (Select one)
- ❍ Some secondary education
- ❍ Secondary education (High School Diploma or equivalent)
- ❍ Technical Degree or Certificate
- ❍ Associate Degree
- ❍ Bachelor's Degree
- ❍ Master's Degree (MA, MS, or equivalent)
- ❍ Master's of Business Administration (MBA or equivalent)
- ❍ PhD, Doctorate, or equivalent
- ❍ MD or similar medical doctor degree
- ❍ Multiple advanced degrees at the same level or in different degree paths (such as MA+MS, MD+PhD, or MS+MBA) >>>> Skip to Page 9: What combination of advanced degrees have you earned? (Choose all that apply)
- ❍ Other ____________________

(End of Page 8)

What combination of advanced degrees have you earned? (Choose all that apply)

- ❑ MA or MS
- ❑ More than one MA or MS
- ❑ Master's of Business Administration (MBA)
- ❑ PhD or similar Doctorate
- ❑ More than one PhD or similar Doctorate
- ❑ MD
- ❑ JD or similar law degree

(End of Page 9)

Select the primary application for your research or product(s). (select one)

- ❍ Astronomy
- ❍ Basic Research, Science
- ❍ Biomedical, Medical Imaging, Health Care
- ❍ Chemical and Biological Analysis
- ❍ Communications and Networking
- ❍ Computing Systems, Data Processing
- ❍ Consumer Electronics
- ❍ Defense, Security, Law Enforcement
- ❍ Displays: Consumer, Information, Entertainment
- ❍ Earth Sciences, Environmental Monitoring, Climate
- ❍ Education and Training
- ❍ Industrial Sensing and Measurement
- ❍ Laser Industry
- ❍ Lighting and Illumination
- ❍ Machine Vision, Factory Automation
- ❍ Materials Processing, Lasers in Manufacturing
- ❍ Optical Data Storage
- ❍ Optics Design and Engineering
- ❍ Optics Manufacturing
- ❍ Semiconductor Manufacturing
- ❍ Solar and Alternative Energy
- ❍ Structural and Infrastructure Sensing
- ❍ Vehicle Sensing and Control
- ❍ Other ____________________

(End of Page 10)

How many years have you worked at your current job? (select one)
- ❍ Less than one year
- ❍ 1-2 years
- ❍ 3-5 years
- ❍ 6-10 years
- ❍ 11-15 years
- ❍ 16-20 years
- ❍ 21-25 years
- ❍ 26-30 years
- ❍ More than 30 years

How did you find your current or original position at your present employer? (select one)
- ❍ Printed job advertisement (newspaper or journal)
- ❍ Online job advertisement
- ❍ In-person job fair
- ❍ University career office
- ❍ Alumni network
- ❍ Professional association
- ❍ I was recruited
- ❍ Private placement agency
- ❍ Public/government placement agency
- ❍ Networking or referral through personal contact
- ❍ I contacted the employer directly (no job was advertised)
- ❍ Other ________________________________

How many years, total, have you been professionally employed? (select one)
- ❍ None
- ❍ Less than 5 years
- ❍ 5-10 years
- ❍ 11-15 years
- ❍ 16-20 years
- ❍ 21-25 years
- ❍ 26-30 years
- ❍ More than 30 years

(End of Page 11)

Please indicate the degree to which you agree or disagree with the following statements about your job.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I am paid fairly for the work I do	❍	❍	❍	❍	❍
I respect the work of my peers	❍	❍	❍	❍	❍
My supervisor is highly competent	❍	❍	❍	❍	❍
My work is meaningful	❍	❍	❍	❍	❍
When I do good work, I receive proper recognition from supervisors and coworkers	❍	❍	❍	❍	❍
I have good opportunities for promotion within my organization	❍	❍	❍	❍	❍
I have the autonomy and independence I need to do my best work	❍	❍	❍	❍	❍
I work too many hours each week	❍	❍	❍	❍	❍
I enjoy my work	❍	❍	❍	❍	❍
Health care and pension benefits are an important part of my compensation	❍	❍	❍	❍	❍

(End of Page 12)

Please indicate the degree to which you agree or disagree with the following statement about your job.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I love my work and I feel fortunate to get paid for doing it.	❍	❍	❍	❍	❍

(End of Page 13)

Please select the currency in which you are paid.

- ❍ Afghan afghani
- ❍ Albanian lek
- ❍ Algerian dinar
- ❍ Angolan kwanza
- ❍ Argentine peso
- ❍ Armenian dram
- ❍ Aruban florin
- ❍ Australian dollar
- ❍ Azerbaijani manat
- ❍ Bahamian dollar
- ❍ Bahraini dinar
- ❍ Bangladeshi taka
- ❍ Barbadian dollar
- ❍ Belarusian ruble
- ❍ Belize dollar
- ❍ Bermudian dollar
- ❍ Bhutanese ngultrum
- ❍ Bolivian boliviano
- ❍ Bosnia and Herzegovina convertible mark
- ❍ Botswana pula
- ❍ Brazilian real
- ❍ British pound
- ❍ Brunei dollar
- ❍ Bulgarian lev
- ❍ Burmese kyat
- ❍ Burundian franc
- ❍ Cambodian riel
- ❍ Canadian dollar
- ❍ Cape Verdean escudo
- ❍ Cayman Islands dollar
- ❍ Central African CFA franc
- ❍ CFP franc
- ❍ Chilean peso
- ❍ Chinese yuan
- ❍ Colombian peso
- ❍ Comorian franc
- ❍ Congolese franc
- ❍ Costa Rican colón
- ❍ Croatian kuna
- ❍ Cuban convertible peso
- ❍ Cuban peso
- ❍ Czech koruna
- ❍ Danish krone
- ❍ Djiboutian franc
- ❍ Dominican peso
- ❍ East Caribbean dollar
- ❍ Egyptian pound
- ❍ Eritrean nakfa
- ❍ Ethiopian birr
- ❍ Euro
- ❍ Falkland Islands pound
- ❍ Fijian dollar
- ❍ Gambian dalasi
- ❍ Georgian lari
- ❍ Ghana cedi

- Gibraltar pound
- Guatemalan quetzal
- Guinean franc
- Guyanese dollar
- Haitian gourde
- Honduran lempira
- Hong Kong dollar
- Hungarian forint
- Icelandic króna
- Indian rupee
- Indonesian rupiah
- Iranian rial
- Iraqi dinar
- Israeli new shekel
- Jamaican dollar
- Japanese yen
- Jordanian dinar
- Kazakhstani tenge
- Kenyan shilling
- Kuwaiti dinar
- Kyrgyzstani som
- Lao kip
- Latvian lats
- Lebanese pound
- Lesotho loti
- Liberian dollar
- Libyan dinar
- Lithuanian litas
- Macanese pataca
- Macedonian denar
- Malagasy ariary
- Malawian kwacha
- Malaysian ringgit
- Maldivian rufiyaa
- Mauritanian ouguiya
- Mauritian rupee
- Mexican peso
- Moldovan leu
- Mongolian tögrög
- Moroccan dirham
- Mozambican metical
- Namibian dollar
- Nepalese rupee
- Netherlands Antillean guilder
- New Zealand dollar
- Nicaraguan córdoba
- Nigerian naira
- North Korean won
- Norwegian krone
- Omani rial
- Pakistani rupee
- Panamanian balboa
- Papua New Guinean kina
- Paraguayan guaraní
- Peruvian nuevo sol
- Philippine peso

- ❍ Polish złoty
- ❍ Qatari riyal
- ❍ Romanian leu
- ❍ Russian ruble
- ❍ Rwandan franc
- ❍ Saint Helena pound
- ❍ Salvadoran colón
- ❍ Samoan tālā
- ❍ São Tomé and Príncipe dobra
- ❍ Saudi riyal
- ❍ Serbian dinar
- ❍ Seychellois rupee
- ❍ Sierra Leonean leone
- ❍ Singapore dollar
- ❍ Solomon Islands dollar
- ❍ Somali shilling
- ❍ South African rand
- ❍ South Korean won
- ❍ Sri Lankan rupee
- ❍ Sudanese pound
- ❍ Surinamese dollar
- ❍ Swazi lilangeni
- ❍ Swedish krona
- ❍ Swiss franc
- ❍ Syrian pound
- ❍ Taiwan new dollar
- ❍ Tajikistani somoni
- ❍ Tanzanian shilling
- ❍ Thai baht
- ❍ Tongan paʻanga
- ❍ Trinidad and Tobago dollar
- ❍ Tunisian dinar
- ❍ Turkish lira
- ❍ Turkmenistani manat
- ❍ Ugandan shilling
- ❍ Ukrainian hryvnia
- ❍ United Arab Emirates dirham
- ❍ United States dollar
- ❍ Uruguayan peso
- ❍ Uzbekistani som
- ❍ Vanuatu vatu
- ❍ Venezuelan bolívar
- ❍ Vietnamese đồng
- ❍ West African CFA franc
- ❍ Yemeni rial
- ❍ Zambian kwacha
- ❍ Zimbabwean dollar

What was your total 2011 annual pre-tax earnings at your current job*, including all salary and bonuses?

Please enter the amount in the currency in which you are paid and do not enter any symbols.
Example: 12000
Total 2011 pre-tax earnings: ______________________________

*SPIE realizes that different countries' tax rates affect net pay, and that differences exist regarding vacation time and other benefits, but for the purposes of this survey, please enter your pre-tax earnings for 2011 including salary and bonuses.

(End of Page 14)

You have indicated that your total 2011 pre-tax pay and bonuses was **%[Pre-tax earnings]Q13_1% %[Please select the currency in which you are paid.]Q2LBL%**.

If that information is correct, click Next below.

If that information is not correct, please click the back arrow of your browser to revise the information on the previous page.

(End of Page 15)

Do you have any other thoughts that you would like to share with the SPIE staff? (Optional)

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If you would like a pre-release copy of the SPIE Global Salary Survey Report and to be entered into the drawing for a free iPad2, please enter your email address below.

Answering this question is optional. SPIE does not share email addresses. Any identifying information is kept strictly confidential. Duplicate entries will be deleted.

Email address: __________________________________

Please click on the *Submit* button below to complete the survey.

The SPIE Team thanks you for your participation.

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