The Pitfalls of Using Location Quotients to Identify Clusters and Represent Industry Specialization in Small Regions

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The Pitfalls of Using Location Quotients to Identify Clusters and Represent Industry Specialization in Small Regions*

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Abstract

This paper examines the use of location quotients, a measure of regional business activity relative to the national benchmark, as an indicator of sectoral agglomeration in small cities and towns, and as a measure of industry specialization that might impact the number of new business startups in these places. Using establishment-level data on businesses located in Maine, our findings suggest that the addition of one "hypothetical" establishment in very small towns leads to a dramatic change in the magnitude of the region-industry location quotient. At population sizes of about 4,100 or more people, however, location quotients are reasonably stable. Regression results from an analysis of the relationship between new business activity and regional industry specialization show that the effect of location quotients on business startups switches from "inelastic" to "elastic" at a population size cutoff of about 2,600 residents. Overall, our findings suggest that researchers and practitioners should exercise caution when using location quotients to study small regions.

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1 Introduction

The location quotient is one of the oldest and most popular measures of state and local industry structure used in the study and practice of regional analysis and policy. The location quotient measures the amount of activity in a region's industrial sector (for example, the percentage of overall employment or establishments) relative to a national benchmark, where a location quotient value of greater than one suggests that the region has a specialization in the sector. Location quotients are used to identify sectors that are clustered in a given place (Carroll et al., 2008; Porter, 1990; O'Donoghue and Gleave, 2004; Tian, 2013). When using them to uncover clusters and "pick winners," the emphasis is often on calling out the actual sectors with high values of the location quotient (Crawley and Hallowell, 2021). Since regional industry specialization can result in cost savings to firms, location quotients are also used to represent localization economies and places that provide a thick labor market, a ready supply of specialized inputs and machinery, and facilitate the flow of knowledge spillovers (De Propris, 2005; Marshall, 1920). When used as a measure of industry specialization, researchers often examine the effect of location quotients on other regional indicators such as industry employment change or new business startups (Artz et al., 2016; Bagchi-Sen et al., 2020; Fracasso and Vittucci Marzetti, 2018; Gabe, 2003; Glaeser et al., 1992).

By their construction, location quotients are sensitive to the level of industry aggregation, how regions are defined, and the choice of the benchmark. For example, the analysis of location quotients at a highly aggregated industry level (e.g., Manufacturing, Financial Services) may not provide evidence of industry agglomeration (i.e., the industry location quotient may be less than or equal to 1.0), even though the region may specialize in a narrowly defined sector. Likewise, the analysis of location quotients in small cities and towns is often complicated by relatively low populations and thus may provide evidence of industry specialization (i.e., location quotient greater than 1.0) with only one or a few businesses operating in the region-industry pair.

This paper examines the utility of location quotients as both an indicator of sectoral agglomeration in small places and as a measure of industry specialization that might impact the number new business startups in a region-industry pair. The analysis uses establishment-level records to calculate location quotients, measured as of 2014, in Maine cities and towns, as well as the number of new business startups per industry in these places between 2014 and 2017. Our findings suggest that location quotients are not robust (i.e., they are unstable) to the addition of one "hypothetical" establishment in very small towns. At population sizes of about 4,100 or more people, however, location quotients are reasonably stable. In addition,

regression results from an analysis of the relationship between new business activity and regional industry specialization show that the effect of location quotients on business startups switches from "inelastic" to "elastic" at a population size cutoff of about 2,600 residents.

2   Background and Motivation

The widespread use of location quotients in the empirical analysis of regional economies is due to their limited data requirements and ease of interpretation (Isserman, 1977; Tian, 2013). In addition to location quotients, other indicators such as spatial statistics (Carroll et al., 2008; Goetz et al., 2009), the Ellison-Glaeser index (Ellison and Glaeser, 1997) and measures of industry linkages (Delgado et al., 2016; Feser and Bergman, 2000) have been employed in the analysis of industry concentration and regional industry specialization. A key limitation of location quotients, which is the focus of this paper, is their difficulty in identifying industry clusters and accurately measuring industry specialization (Woodward and Guimarães, 2009), particularly in very small regions, due to their small size (Tian et al., 2020). For example, Carroll et al. (2008, p.454) note that "a few auto plants in a rural Indiana county may generate a higher location quotient than the large automobile employment concentration in Wayne County, Michigan." This issue of "a few" establishments generating a misleadingly high location quotient in a small region is very much at the heart of our analysis.

Other often cited limitations of using simple location quotients in empirical research—and these are closely related to (and exasperated by) the "small region problem" described above—are that they are based on a single industry and a single location. It may be incomplete to use location quotients that focus on a single industry because the benefits of clusters and industry localization are due to the presence of a good or service's entire supply chain along with supporting infrastructure and institutions, and a pooled labor force (Porter, 2000). As a way to overcome this limitation and incorporate an industry's supply chain, studies by Feser and Bergman (2000), Feser, Renski and Goldstein (2008), and Yang and Stough (2005) identified clusters based on linkages across multiple sectors of the economy.

An issue related to the use of location quotients that focus on a single region (such as county, town, etc.) is that clusters often straddle administratively defined borders (Duranton and Overman, 2005). In other words, there is no reason why a group of firms that produce a similar good, and businesses that supply related products and services, needs to line up with the geographic boundaries of towns, counties or even states. Related to this issue,

Crawley and Pickernell (2013) examined how different sizes of regions masked the number of clusters identified by the European Cluster Observatory. To address this limitation of location quotients, Carroll et al. (2008) used the Geti's-Ord measure of spatial autocorrelation to identify multi-county indicators of industry clusters, and Tian et al. (2020) employed a spatial input-output location quotient (SI-LQ) that accounts for linkages across county borders.[1]

Another challenge related to the use of location quotients, which is relevant regardless of how sectors or regions are defined, is coming up with an appropriate cutoff to identify industry clusters (i.e., a sufficiently high level of regional industry specialization). By construction, a location quotient value of greater than 1.0 means that an industry's share of total employment (or establishments) in the region of interest exceeds this percentage in the benchmark economy. Following this general guideline, research by De Propris (2005) and Delgado, Porter and Stern (2014) used location quotient cutoffs of 1.25 or higher to identify clusters. In other studies, Crawley, Beynon and Munday (2013), O'Donoghue and Gleave (2004), and Tian (2013) exploit information on the distribution of location quotient values across regions to determine appropriate cutoffs (e.g., upper five percent of the distribution) for identifying high levels of industry specialization.

Building from the existing literature on the pitfalls and limitations of using location quotients to identify clusters and measure industry specialization, we focus on their use in small regions. Although the sectors considered in the analysis are multi-industry groups, which can capture linkages across sectors, the regions are individual cities and towns in Maine. The inclusion of some sparsely populated towns (e.g., less than 100 people) allows us to examine the stability of location quotients in these very small places and as a factor (i.e., industry specialization) affecting the growth of regions. The results suggest that location quotients are unstable in small regions, as well as a poor indicator of industry specialization in these places. This means that the main concern regarding the use of location quotients in very small places is not related to the appropriate cutoff to identify industry clusters. Rather, the tool appears to be an unreliable measure of industry specialization in small regions at any cutoff level of the location quotient, even when extremely high values are observed.

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[1] Also known as hot-spot analysis, the Getis-Ord method can be used to identify regions with a propensity for spatial clustering (Ord and Getis, 1995).

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3 Using Location Quotients to Identify Clusters

A common use of location quotients is to measure industry agglomeration and identify regions with a high specialization in a given industry. Although there are differences in the exact cutoffs used to define clusters (Akgüngör et al., 2003; Carroll et al., 2008; Delgado et al., 2016; Manzini and Luiz, 2019; Mendoza-Velazquez, 2017), location quotients that exceed 2.0 indicate that an industry's percentage of regional employment (or establishments) is more than twice as high as the industry's percentage of employment (or establishments) in the benchmark. A location quotient of, say, 2.5 in an urban county might signify a reasonably large group of businesses that function as a distinct industry cluster, whereas a similar (or even much larger) value of the location quotient in a small town might represent a single, isolated establishment (Carroll et al., 2008).

This paper provides new empirical insights into this problem by examining the utility of location quotients to measure industry agglomeration in small places. Location quotients, based on establishment counts, in 6,110 region-industry pairs in Maine are calculated. The dataset covers 470 cities and towns—ranging in size from fewer than 100 residents to more than 60,000 people—and 13 industry groups.[2] The industry groups, which do not cover all sectors of the economy, are based on classifications used by the Battelle Institute and Maine Technology Institute to study industry clusters in Maine. The industry groups (e.g. Environmental Services, Forestry-Related Products, and Medical Devices) consist of as few as three, and as many as 50, six-digit NAICS codes.[3] They vary in size from industry groups that are a small part (e.g., Boatbuilding and Related Industries) of the benchmark region (i.e., the United States), to groups that are relatively large contributors (Finance and Business Support Services) to the U.S. economy. The number of establishments in the 6,110 region-industry pairs is counted, as of 2014, using Dun and Bradstreet records that were accessed in 2017.[4]

Table 1 shows the top 20 location quotients from the 6,110 region-industry pairs considered in the analysis. Seven region-industry pairs have location quotients that exceed 200, suggesting that an industry's share of establishments in a place is more than 200-times larger than the

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[2]The five largest cities in Maine are Portland (66,317 people), Lewiston (36,410 people), Bangor (32,800 people), South Portland (25,154 people) and Auburn (22,960 people).

[3]For example, the Boatbuilding and Related Industries sector is made up of the Plastics material and resin manufacturing (NAICS: 325211), Synthetic rubber manufacturing (NAICS: 325212), Cellulosic organic fiber manufacturing (NAICS: 325221), Noncellulosic organic fiber manufacturing (NAICS: 325222), and Boat building (NAICS: 336612) industries.

[4]The other data sources used to calculate the region-industry location quotients are described later in the paper.

industry's share of U.S. establishments, and another 12 region-industry pairs have location quotients of between 100 and 200. Although places with a population of 500 or fewer people represent about one-quarter of the towns in the dataset, they account for almost one-half of the region-industry pairs with the highest location quotients.

Isle Au Haut, which has a population of 61 people and a total of eight business establishments, is home to the "largest" industry cluster in Maine. The Alternative Energy and Turbines sector's share of Isle Au Haut establishments is 653-times larger than the industry's share of U.S. businesses. In reality, the cluster consists of a single energy company that supplies electricity to the island. In fact, almost two-thirds of the most highly specialized industry sectors highlighted in Table 1 consist of a single establishment. If that one company were to disappear, the location quotient would fall from values in excess of 100 to zero. Likewise, the location quotient would change dramatically if the industry sector were to grow by one establishment or if a few other businesses (in different sectors) were to begin operations in the region.

To examine the stability of industry location quotients in small cities and towns, we performed an experiment—involving the calculation of "adjusted" location quotients—that added one hypothetical establishment to each of the 13 industry sectors in all 470 regions. A comparison of the actual and adjusted location quotients shows the extent to which the measure of regional industry agglomeration is impacted by a very small change in the region-industry's size. A one-establishment increase in region-industry size could happen if a new business located in the area, or even as a result of an administrative misclassification of an establishment's industry sector and/or a miscounting of businesses located in a region. Crawley, Beynon and Munday (2013) note that, in some applications of location quotients, publicly available employment figures and establishment counts may be imputed estimates rather than direct figures. In a small rural area, where data are more often to be suppressed, an estimated figure that varies from the region-industry's actual size (by even a small amount) can have a sizable impact on the location quotient.

For example, equations 1 and 2 show the calculations for the actual and adjusted location quotients, focusing on Isle Au Haut's Alternative Energy and Turbines sector:

$$LQ = \frac{(X_{ir}/X_r)}{(X_{iN}/X_N)} = \frac{(1/8)}{(1,448/7,563,084)} = 653 \tag{1}$$

$$LQ_{adj} = \frac{(X_{ir}+1)/(X_r+13)}{(X_{iN}+1)/(X_N+13)} = \frac{(2/21)}{(1,449/7,563,097)} = 497 \tag{2}$$

where, X represents the number of business establishments, the subscript "i" indexes the industry sector (e.g., Alternative Energy and Turbines), the subscript "r" indexes the region (e.g., Isle Au Haut) and the subscript "N" represents the benchmark economy (e.g., the United States)

The adjusted location quotient (497) is approximately 31 percent lower than the actual (simple) location quotient (653).[5] This large difference calls into question whether location quotients can convey reliable information about industry agglomeration at this level of sectoral aggregation for a small town such as Isle Au Haut. Table 2 shows the actual and adjusted location quotients for all 13 of the industry sectors in Isle Au Haut, where the difference between the two measures is squared to exaggerate larger differences and translate negative differences into positive values. The average squared difference between the actual and adjusted location quotients is 4,683 in Isle Au Haut, when we performed the experiment of adding one establishment to each of the 13 industry sectors.

To expand the analysis across a wider range of small regions, we compare the actual and adjusted location quotients for all 6,110 region-industry pairs in Maine. The city- and town-level data used to calculate the location quotients, as of 2014, are from Dun and Bradstreet establishment records in Maine (accessed in 2017), and the numbers of establishments in the benchmark (i.e., United States) industry and region are counted using County Business Patterns data. Figure 1 shows how the city- and town-level average squared difference between actual and adjusted location quotients varies with population size. The results show that our experiment of adding one hypothetical establishment to each region-industry pair leads to very large differences between the actual and adjusted location quotients in places with fewer than 1,000 people, with especially large differences in towns with fewer than 500 residents. For example, in the 117 Maine towns with 500 or fewer people, the average (across the 13 industry sectors) squared difference between actual and adjusted location quotients has a mean value of 9,049, compared with a mean value of 1,197 in the 353 cities and towns with more than 500 people. In the 186 places with fewer than 1,000 people, the average squared difference has a mean value of 6,825, compared with 746 in Maine's cities and towns with more than 1,000 residents.

We can use the data points shown on Figure 1 to estimate the population size at which the average squared difference between the actual and adjusted location quotients is "close" to

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[5]Tian et al. (2020) found even larger differences when they compared maximum values of simple location quotients and their adjusted spatial input-output location quotients (SI-LQ). For example, Patrick County, Virginia, has a simple location quotient value of 738 for the Fishing, Hunting and Trapping sector (NAICS 114), whereas—after accounting for input-output relationships and linkages across county borders—the maximum SI-LQ for the Fishing, Hunting and Trapping sector falls to 9.66 in St. Bernard Parish, Louisiana.

zero. This can be thought of as a population threshold above which the location quotient is reasonably stable to a small change in region-industry size. To estimate this threshold, we calculate 95-percent confidence intervals around the average squared difference and find the population size at which the interval's lower bound is equal to (or less than) zero. Figure 2 shows a 95-percent confidence interval for the average squared difference, which is calculated using data for the town of interest and the 25 next smallest and 25 next largest municipalities. For example, the 51 towns used to estimate the confidence interval for the Town of Jonesboro (population size of 495 residents) range in size from 403 to 643 people. The average squared difference between the actual and adjusted location quotients, across these 51 towns, has a mean value of 3,955 with a standard deviation of 2,455. This gives a 95-percent confidence interval of 3,265 to 4,645. The point on the x-axis of Figure 2 at which the interval's lower bound passes through zero corresponds with a population size of 4,076 residents.

4   Using Location Quotients to Measure the Impacts of Industry Specialization

Along with their widespread use in measuring sectoral agglomeration, location quotients are also commonly included in regional growth models to represent localization economies (e.g., pooled labor force, availability of specialized inputs, knowledge spillovers) that arise from a high regional specialization of industry (Fracasso and Vittucci Marzetti, 2018). Other research has used location quotients to measure new firm startups in a region-industry pair (Artz et al., 2016; Cader and Leatherman, 2008; Delgado et al., 2014; Gabe, 2003) and studies have used the location quotient to analyze the relationship between regional industry specialization and growth (Chikán et al., 2008; Gabe, 2017; Glaeser et al., 1992; Kemeny and Storper, 2015).

Because, as demonstrated above, high values of the location quotient may not necessarily indicate a high level of industry agglomeration in a small place, their use in regional growth models could provide a misleading impression of the effects of industry specialization. To investigate this idea, we estimate a simple firm location model focusing on the same region-industry pairs as used in the analysis of the difference between the actual and adjusted location quotients. The dependent variable in the firm location model is the number of new

businesses per region-industry pair. These new companies were identified using Dun and Bradstreet files for Maine, with the businesses having start dates between 2014 and 2017.[6]

Table 3 presents descriptive statistics of the variables used in the empirical model of new business startups. Although the explanatory variable of primary interest is the region-industry location quotient, the regression model also controls for the effects of population size (a measure of urbanization), the share of the population with a bachelor's degree or higher (a measure of human capital), the region's accessibility to markets as represented by the driving time to the nearest metropolitan area in Maine (i.e., Bangor, Lewison-Auburn or Portland), and the municipality's property tax rate and government spending per capita (two local policy variables). In addition, the new business startup model includes dummy variables representing a town's location in one of Maine's 16 counties and dummy variables for the 13 industry sectors. These two sets of dummy variables are used to control for the wide variation in new business activity across regions of Maine (e.g., Cumberland County has 270 new startups, compared with 43 in Penobscot County) and by industry sector (the Agriculture, Aquaculture, Fisheries, and Food Production sector has 323 new businesses, compared with 64 in the Forestry-Related Products industry).

The analysis of new business startups uses a negative binomial regression model, which is an appropriate estimator given the count nature of the dependent variable and the fact that the variance of new business startups per town-industry pair (0.8) well exceeds (i.e., overdispersion) the mean value of 0.14. (Alañón-Pardo and Arauzo-Carod, 2013; Gabe and Bell, 2004; Guimaraes et al., 2003). Regression results shown in Table 4 are marginal effects from the negative binomial regression model and, in the analysis, the location quotient is interacted with the 13 industry dummy variables to allow for heterogeneity in the impacts across the different sectors. The first column of results is from a regression that uses data on the entire sample of 6,006 region-industry pairs, and the marginal effect of interest shows that a one-unit increase in the location quotient is associated with a 0.05-unit increase in the number of new businesses between 2014 and 2017 per region-industry pair. Other results show that a region's population size and the percentage of residents with a bachelor's degree or higher have positive and statistically significant impacts on the number of new business startups, which suggest that "urbanization" and human capital are important to business location.

Given our results that suggest the location quotient is an unreliable indicator of industry specialization in small towns, we re-estimate the regression model at several population cutoff

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[6]This means that, in order for a company to be counted as a new business that started between 2014 and 2017, it needed to have remained in operation until at least 2017.

thresholds to demonstrate the influence of removing observations from small regions. For example, a population cutoff of 1,000 people removes the 186 smallest Maine towns from the sample (39.6 percent of the observations), whereas a cut-off of 10,000 people removes 452 places (96.2 percent of the observations). The last four columns of Table 4 show marginal effects, which are estimated using the negative binomial regression model, when population cutoffs are implemented. After removing the smallest towns (i.e., less than 1,000 people) from the sample, the marginal effect corresponding with the location quotient increases from 0.05 to 0.09 new establishments per region-industry pair. Using a population cutoff of 4,000 people, which removes 383 of the 470 cities and towns, the regression results show that a one-unit increase in the location quotient is associated with an additional 0.31 new business startups per region-industry pair. The pattern of an increase in the size of the marginal effect corresponding with the location quotient at larger population cutoff values increases up to (and beyond) 10,000 people (marginal effect of 1.13), although the impact of the location quotient on new business startups is not statistically significant at a one-percent level.

Figure 3 shows the marginal effects corresponding to the region-industry location quotients across the entire distribution of population size cutoff values. The marginal effects are positive and generally statistically significant up to a population size cutoff of about 5,000 people. Beyond this threshold, the marginal effects of the location quotient on the number of new business openings are not generally statistically significant at a one-percent level. For example, 139 of the 141 population cutoff values of 5,000 people or less have statistically significant (at the one-percent level) marginal effects corresponding with the location quotient, compared with one of the 43 population cutoff values of more than 5,000 residents. In addition, whereas the pattern in Figure 3 shows a gradual increase in the marginal effect corresponding with the location quotient from a population size cutoff of zero to about 5,000 residents, the marginal effects are considerably more scattered at population size cutoff values that are greater than about 6,000 people.

These results suggest that the positive and statistically significant effects of the location quotient on the number of new business startups are identified by having a mix of larger and smaller places in the regression model. That is, an analysis focusing only on the top end of the distribution of region population size (e.g., those with over 5,000 people) does not generally register a statistically significant effect (at a one-percent level) of industry specialization on new business activity. Rather, it requires the inclusion of smaller and larger places to capture the positive effects of industry specialization on the number of new

business startups.[7] The results showing that the location quotient is an unreliable indicator of industry specialization in very small places, combined with the finding that a mix of small and large regions is needed to identify a positive and statistically significant effect of location quotients on new business startups, suggests a delicate balance when selecting a population size cutoff to use in the analysis.[8]

As a way to make more consistent comparisons across the population size cutoff values, Figure 4 shows the elasticity of new business startups with respect to the location quotient (instead of the marginal effect). In this figure, we include the population size cutoff values for which there is a statistically significant relationship (at the one-percent level) between new business startups and the region-industry location quotient. The figure shows a very distinct break at a population size cutoff of 2,600 or more people. At population size cutoffs of 2,600 or more residents, the effect of the location quotient on new business startups is elastic. In other words, an increase in the location quotient of a given percentage change is met with an even larger percentage increase in the number of new business startups. At population size cutoff values of less than 2,600, the elasticity of new business startups with respect to the location quotient is less than 1.0 (i.e., inelastic) in 53 of the 92 observations (58 percent), and the elasticity is less than 0.90 in 42 percent of the observations. The average elasticity value is 1.27 across the size population cutoffs of 2,600 or more people, and 0.95 at population size cutoffs of below 2,600 residents.

5   Conclusions

Due in part to its modest data requirements, and straightforward and intuitive interpretation, the industry location quotient is used extensively in regional economic analysis. Despite this widespread use, researchers have noted several limitations of "simple" location quotients, including their weakness at identifying clusters that cross industry and geographic borders (Feser et al., 2008; Tian et al., 2020), and the difficulty in determining an appropriate cutoff of the location quotient for identifying industry clusters (Crawley et al., 2013; O'Donoghue and Gleave, 2004). Likewise, studies have noted the pitfalls and limitations of using location quotients to measure regional specialization in very small places (Carroll et al., 2008).

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[7]Along with omitting data from the lesser-populated towns, the analysis focusing on larger places has a smaller sample size, which increases the standard errors of the marginal effects.

[8]Our finding of a statistically significant marginal effect of the location quotient up to a population size cutoff of about 5,000 people is probably unique to Maine (and other small states), which has a relative lack of cities and towns with population sizes above this threshold.

In this paper, we examined the use of location quotients in small cities and towns—both as a way to measure industry agglomeration and to represent the benefits of regional industry specialization in the analysis of new business startups. Our results from both parts of the analysis show that location quotients are an unreliable indicator in small regions. First, a list compiled of the highest location quotients in Maine region-industry pairs shows some values that are far in excess of 100, which suggest that a sector's share of all establishments in a given region is more than 100-times larger than the sector's share of all establishments in the U.S. economy. The vast majority of these unusually high location quotients, however, are the result of a single establishment in a very small place.

Second, an experiment that involved adding one hypothetical establishment to region-industry pairs in Maine led to very large differences between the actual and adjusted location quotients in places with populations of less than about 1,000 people. Populations sizes of about 4,100 or more residents are needed for these differences to become negligible. Given the difficulty in coming up with accurate industry establishment counts in small places (and large regions, for that matter) and the possibility of misclassification of businesses, the large swings in the location quotient from adding just a single establishment make them particularly unstable and unreliable in small places.

Third, moving to an analysis of the effects of industry specialization on new business activity, we find that the relationship between business startups and the location quotient switches from "inelastic" to "elastic" at a population cutoff size of about 2,600 or more people. This pattern of the elasticity of new business startups with respect to the location quotient turning from inelastic to elastic at a population size cutoff of about 2,600 residents is likely the result of high location quotients being practically meaningless in very small places. Since a location quotient value of greater than, say, 100 means little more than the presence of a single business in a small town, the estimated effect of the location quotient on new business startups is influenced by very small places with a combination of extremely high location quotients—but not the benefits of a pooled labor force, availability of specialized inputs and machinery, and knowledge spillovers—and low levels of new business activity.

The results from both parts of the analysis suggest that a population cutoff of about 4,100 residents is needed to come up with location quotient values that are not influenced very much by the increase of one business, whereas a cutoff of about 2,600 people is needed to arrive at a reliable estimate of the effect of location quotients on new business startups. These findings, which suggest that a regression analysis of new business startups is less influenced by misleadingly high values of the location quotient, are not surprising. Regression analysis

provides an estimate of an "average" effect, whereas using location quotients to measure the level of industry agglomeration involves looking at "specific" values for region-industry pairs.

With these pitfalls in mind, an approach to studying industry clusters and regional specialization in small places is to combine nearby places into larger regions. For example, studies by Carroll et al. (2008) and Tian et al. (2020) outline approaches to identify multi-region indicators of industry clusters. Although the analysis of multi-town regions limits a researcher or practitioner's ability to describe the industry structure of a specific (small) place, the fact that clusters cross administratively defined borders suggests that a small town—if part of a multi-place region with a high specialization of industry—can contribute to (and capture the benefits of) an industry cluster.

References

Akgüngör, S., Kumral, N., and Lenger, A. (2003). National industry clusters and regional specializations in turkey. *European Planning Studies*, 11(6):647–669.

Alañón-Pardo, A. and Arauzo-Carod, J.-M. (2013). Agglomeration, accessibility and industrial location: Evidence from spain. *Entrepreneurship Regional Development*, 25(3):135–173.

Artz, G. M., Kim, Y., and Orazem, P. F. (2016). Does agglomeration matter everywhere? new firm location decisions in rural and urban markets. *Journal of Regional Science*, 56(1):72–95.

Bagchi-Sen, S., Schunder, T., and Tai, X. (2020). An analysis of employment patterns of domestic migrants and immigrants in a rustbelt city: A study of buffalo-niagara falls. *Growth and Change*, 51(1):123–143.

Cader, H. A. and Leatherman, J. C. (2008). Geography of employment and establishment dynamics in information technology and e-commerce industries. *Journal of Regional Analysis and Policy*, 38(1):1–18.

Carroll, M. C., Reid, N., and Smith, B. W. (2008). Location quotients versus spatial auto-correlation in identifying potential cluster regions. *Ann Reg Sci*, 42(2):449–463.

Chikán, A., Sölvell, , Ketels, C., and Lindqvist, G. (2008). Industrial specialization and regional clusters in the ten new EU member states. *Competitiveness Review: An International Business Journal incorporating Journal of Global Competitiveness*, 18:104–130.

Crawley, A., Beynon, M., and Munday, M. (2013). Making location quotients more relevant as a policy aid in regional spatial analysis. *Urban Studies*, 50(9):1854–1869.

Crawley, A. and Hallowell, A. (2021). Smart specialisation: insights from the north american periphery. *Regional Studies*, 55(3):427–440.

Crawley, A. and Pickernell, D. (2012). An appraisal of the european cluster observatory. *European Urban and Regional Studies*, 19(2):207–211.

De Propris, L. (2005). Mapping local production systems in the UK: Methodology and application. *Regional Studies*, 39(2):197–211.

Delgado, M., Porter, M. E., and Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy*, 43(10):1785–1799.

Delgado, M., Porter, M. E., and Stern, S. (2016). Defining clusters of related industries. *Journal of Economic Geography*, 16(1):1–38.

Duranton, G. and Overman, H. G. (2005). Testing for localization using micro-geographic data. *The Review of Economic Studies*, 72(4):1077–1106.

Ellison, G. and Glaeser, E. (1997). Geographic concentration in u.s. manufacturing industries: A dartboard approach. *Journal of Political Economy*, 105(5):889–927.

Feser, E., Renski, H., and Goldstein, H. (2008). Clusters and economic development outcomes: An analysis of the link between clustering and industry growth. *Economic Development Quarterly*, 22(4):324–344.

Feser, E. J. and Bergman, E. M. (2000). National industry cluster templates: A framework for applied regional cluster analysis. *Regional Studies*, 34(1):1–19.

Fracasso, A. and Vittucci Marzetti, G. (2018). Estimating dynamic localization economies: the inadvertent success of the specialization index and the location quotient. *Regional Studies*, 52(1):119–132.

Gabe, T. (2003). Local industry agglomeration and new business activity. *Growth and Change*, 34(1):17–39.

Gabe, T. and Bell, K. (2004). Tradeoffs between local taxes and government spending as determinants of business location. *Journal of Regional Science*, 44(1):21–41.

Gabe, T. M. (2017). *The Pursuit of Economic Development: Growing Good Jobs in U.S. Cities and States*. Palgrave Macmillan.

Glaeser, E., Kallal, H., Scheinkman, J., and Shleifer, A. (1992). Growth in cities. *Journal of Political Economy*, 100(6):1126–1152.

Goetz, S. J., Shields, M., and Wang, Q. (2009). Identifying food industry clusters: A comparison of analytical tools. *Targeting Regional Economic Development*, pages 281–310.

Guimaraes, P., Figueirdo, O., and Woodward, D. (2003). A tractable approach to the firm location decision problem. *The Review of Economics and Statistics*, 85:201–204.

Haig, R. M. (1926). Toward an understanding of the metropolis: I. some speculations regarding the economic basis of urban concentration. *The Quarterly Journal of Economics*, 40(2):179–208.

Isserman, A. M. (1977). The location quotient approach to estimating regional economic impacts. *Journal of the American Institute of Planners*, 43(1):33–41.

Kemeny, T. and Storper, M. (2015). Is specialization good for regional economic development? *Regional Studies*, 49(6):1003–1018.

Lester, T., Lowe, N., and Freyer, A. (2012). Mediating incentive use: A time-series assessment of economic development deals in north carolina. *Economic Development Quarterly*, 28.

Manzini, R. B. and Luiz, D. S. C. (2019). Cluster identification: A joint application of industry concentration analysis and exploratory spatial data analysis (ESDA). *Competitiveness Review: An International Business Journal*, 29(4):401–415.

Marshall, A. (1920). *Principles of economics; an introductory volume*. Macmillan.

Mendoza-Velazquez, A. (2017). The effect of industrial competition on employment: A porter's approach to the study of industrial clusters in mexico. *Competitiveness Review: An International Business Journal*, 27(4):410–432.

Ord, J. K. and Getis, A. (1995). Local spatial autocorrelation statistics: Distributional issues and an application. *Geographical Analysis*, 27(4):286–306.

O'Donoghue, D. and Gleave, B. (2004). A note on methods for measuring industrial agglomeration. *Regional Studies*, 38(4):419–427.

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, pages 73–91.

Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly*, 14(1):15–34.

Tian, Z. (2013). Measuring agglomeration using the standardized location quotient with a bootstrap method. *Journal of Regional Analysis and Policy*, 43:186–197.

Tian, Z., Gottlieb, P. D., and Goetz, S. J. (2020). Measuring industry co-location across county borders. *Spatial Economic Analysis*, 15(1):92–113.

Woodward, D. and Guimarães, P. (2009). *Porter's Cluster Strategy and Industrial Targeting*, pages 68–83. Routledge.

Yang, G. and Stough, R. (2005). *A Preliminary Analysis of Functional and Spatial Clustering: The Case of the Baltimore Metropolitan Region*, pages 303–320. Edward Elgar.

Table 1: Top 20 Location Quotients in Maine Region-Industry Pairs

Town	Industry Sector	Town Population	Number of Establishments	Location Quotient
Isle Au Haut	Alternative Energy & Turbines	61	1	653
Atkinson	Boatbuilding & Related Industries	249	2	574
Brooklin	Boatbuilding & Related Industries	858	7	539
Atkinson	Alternative Energy & Turbines	249	1	475
Cranberry Isles	Boatbuilding & Related Industries	123	1	316
Beals	Boatbuilding & Related Industries	485	1	263
North Haven	Boatbuilding & Related Industries	410	2	218
Long Island	Boatbuilding & Related Industries	239	1	176
Parsonsfield	Alternative Energy & Turbines	1,746	1	163
Arundel	Alternative Energy & Turbines	4,100	6	159
Westmanland	Agriculture, Aquaculture, Fisheries & Food Production	89	1	157
Carroll Plantation	Forestry-Related Products	115	1	148
Perry	Alternative Energy & Turbines	825	1	145
Southwest Harbor	Boatbuilding & Related Industries	1,976	7	142
Sedgwick	Boatbuilding & Related Industries	1,137	2	132
Exeter	Alternative Energy & Turbines	1,012	1	127
Steuben	Boatbuilding & Related Industries	1,017	2	122
South Bristol	Boatbuilding & Related Industries	952	1	105
Milford	Alternative Energy & Turbines	3,054	1	104
Cushing	Alternative Energy & Turbines	1,415	1	99

Notes: Town population figures are from the U.S. Census Bureau. The number of establishments is counted, as of 2014, using Dun and Bradstreet business records for Maine. When calculating the location quotient, the numbers of establishments in the benchmark (i.e., United States) industry and region are counted using County Business Patterns data. Town population data is obtained from the American Community Survey.

This table shows the 20 largest location quotients for all region-industry pairs in the sample. Although the location quotients are quite large, 65 percent of the region-industry pairs are made up of a single establishment.

Table 2: Actual and Adjusted Town-Industry Location Quotients in Isle Au Haut

Industry Sector	Location Quotient	Adjusted LQ	Difference Squared
Alternative Energy & Turbines	653	497	24,165
Agriculture, Aquaculture, Fisheries & Food Production	20	15	22
Biopharmaceuticals	0	40	1,603
Boatbuilding & Related Industries	0	150	22,631
Defense	0	87	7,630
Electronics & Semiconductors	0	34	1,155
Engineering & Scientific/Technical Services	0	4	18
Environmental Services	0	13	166
Finance & Business Support Services	0	1	1
Forestry-Related Products	0	7	50
Information Technology Services	0	2	5
Materials for Textiles, Apparel, Leather & Footwear	0	9	87
Medical Devices	0	58	3,348
Average			4,683

Notes: Location quotients are calculated using Dun and Bradstreet business records for Maine, and the numbers of establishments in the benchmark (i.e., United States) industry and region are counted using County Business Patterns data.

This table demonstrates the average difference squared methodology on the 13 industrial sectors on Isle Au Haut. When a hypothetical establishment is added to each of the industrial sectors in the region, the location quotients change drastically, with the largest LQ decreasing by over 30%. The experiment demonstrates how unstable a location quotient in a small region could be.

Table 3: Descriptive Statistics of Variables Used to Analyze New Business Startups in Maine

Variable	Description	Mean	St.Dev.	Min.	Max.
New Business	Number of new businesses per region-industry pair between 2014 and 2017	0.14	0.91	0	50
Location Quotient	Region-industry location quotient, 2014	2.8	18.34	0	653
Population	Natural log of population size, 2014	7.05	1.42	2.4	11.1
College Degree	Percentage of population with at least a college degree, 2014	0.32	0.12	0.00	0.73
Tax Rate	Municipal property tax rate, 2014	0.02	0.01	$6.8e^{-4}$	0.03
Local Gov't Spend	Municipal government spending per resident, measured in $1,000s, 2014	2.03	2.53	0.05	44.5
Distance to Metro	Driving time to near metropolitan area in Maine (Bangor, Lewiston-Auburn, Portland)	69.2	43.0	0.0	227

Notes. Data for the Population and College Degree variables are from the 5-year sample of the 2014 American Community Survey. Data for the Tax Rate and Local Gov't Spending variables are from the Maine Revenue Services 2014 Statistical Summary. A town's driving time to the nearest Maine metropolitan area (i.e., Distance to Metro) is calculated using the gmapsdistance R package. The descriptive statistics are based on 6,110 observations for the New Business, Location Quotient and Tax Rate variables, 6,097 observations for the Population, College Degree and Local Gov't Spend variables, and 6,019 observations for the Distance to Metro variable.

Table 4: Marginal Effects of Region-Industry Location Quotient on New Business Startups in Maine: Negative Binomial Estimator

		Population Size Cutoff			
Variable	No Cutoff	1,000 People	2,000 People	4,000 People	10,000 People
Location Quotient	0.05**	0.09**	0.12*	0.31**	1.13
	(0.01)	(0.02)	(0.04)	(0.09)	(0.47)
Population	0.15**	0.23**	0.35**	0.57**	2.09**
	(0.01)	(0.02)	(0.04)	(0.07)	(0.30)
College Degree	0.27**	0.35*	0.46	0.51	3.77*
	(0.07)	(0.12)	(0.20)	(0.41)	(1.44)
Tax Rate	2.41	3.91	5.07	5.04	44.90
	(1.63)	(2.53)	(4.47)	(7.63)	(31.04)
Local Gov't Spend	-0.01	-0.01	-0.01	-0.02	-0.14
	(0.01)	(0.02)	(0.03)	(0.07)	(0.27)
Distance to Metro	0.00	0.00	0.01	0.15	1.50
	(0.03)	(0.05)	(0.07)	(0.14)	(0.95)
Number of Observations	6,006	3,692	2,145	1,131	234

Notes. The superscripts ** and * indicate statistical significance at the 0.1- and 1-percent levels, respectively. Robust standard errors are shown in parentheses. The regression models include dummy variables indicating the town's county of location, and dummy variables for the 13 industries. The model also includes variables that measure the interaction between the industry location quotient and the 13 industry cluster dummy variables to allow for heterogeneity in the impacts across the sectors.

This table shows the regression results at various population cutoffs. In this analysis, the location quotient is interacted with the 13 industry dummy variables to allow for heterogeneity in the impacts across the sectors. As larger population cutoffs are implemented, a pattern of increasing marginal effects corresponding to the location quotient emerges. However, at a population size cutoff of 4,000, the significance of the variable begins to diminish, as the number of observations drops below 1,200.
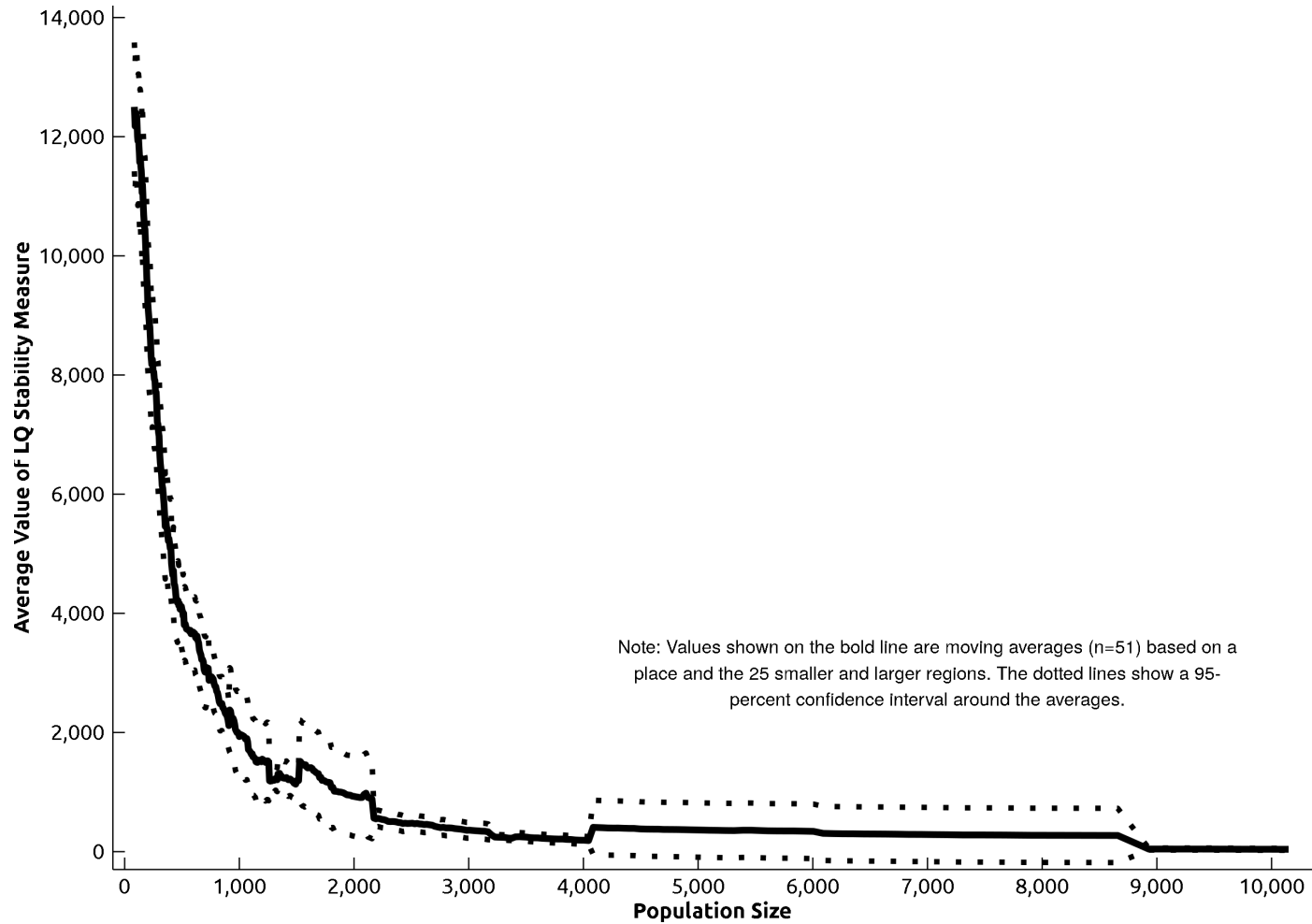
Figure 1: Location Quotients are Unstable in Small Cities and Towns.
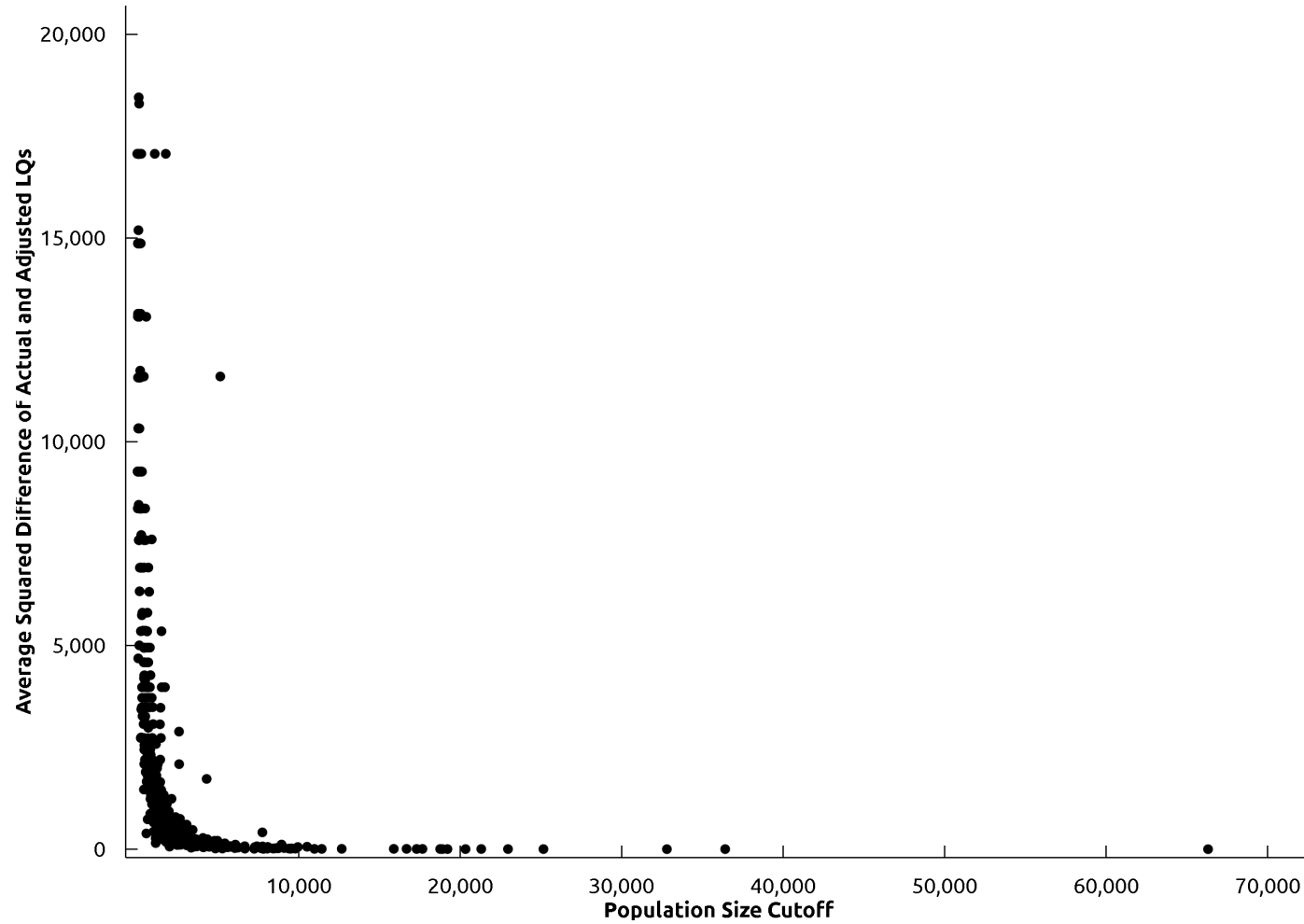
This figure shows the average difference squared between the location quotient and adjusted location quotient, calculated by adding a hypothetical establishment to each region-industry pair, for each region in the data, graphed against that region's population size. The average squared difference variable (plotted on the vertical axis) decreases sharply as the population size cutoff (plotted on the horizontal axis) increases. This experiment demonstrates the potential instability of the location quotient as a measure of localization in small localities.

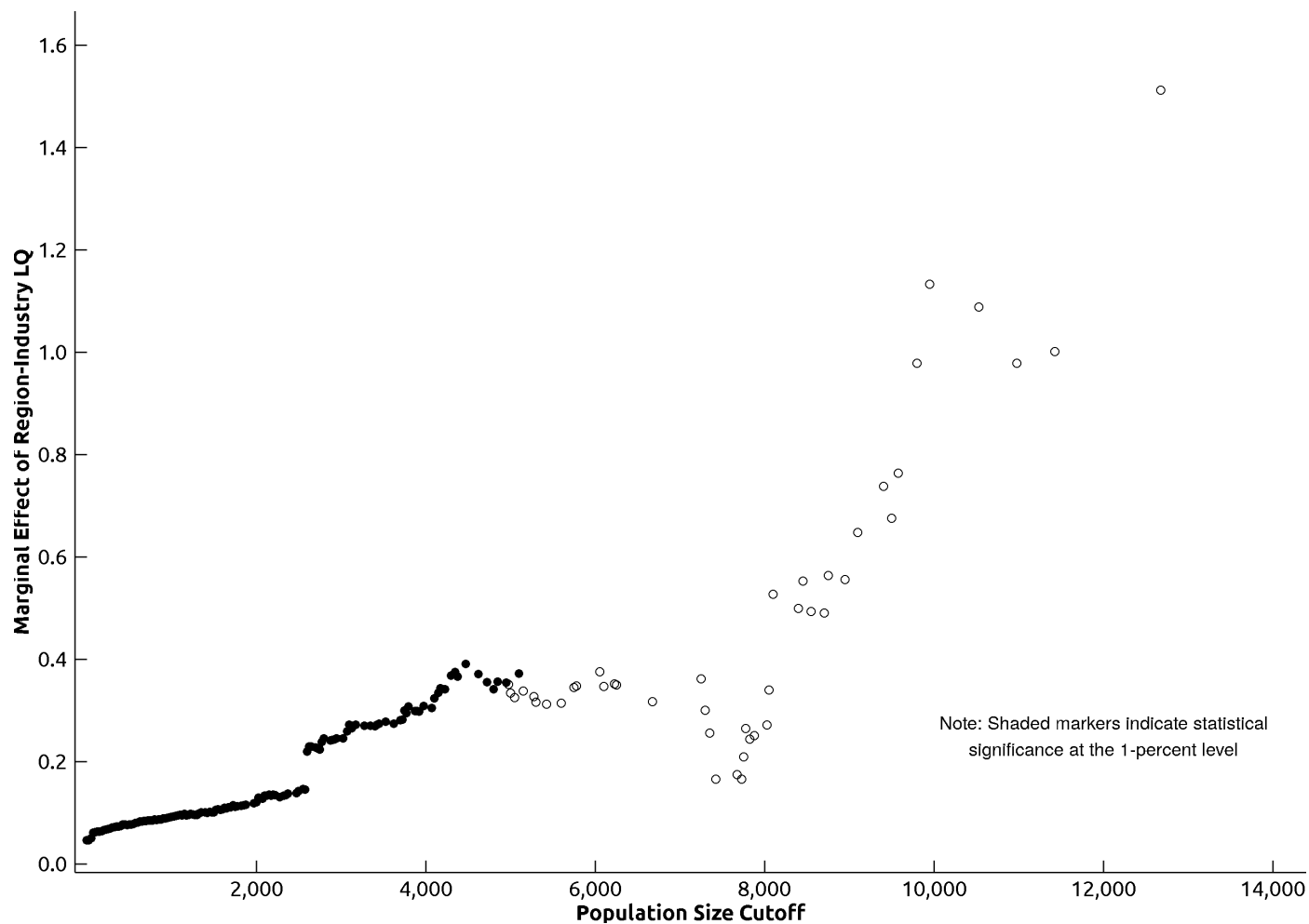Source: Dun & Bradstreet, County Business Patterns, American Community Survey, and authors' calculations.

Figure 2: Location Quotients are Reasonably Stable in Places with 4,100 or More People

Note: Values shown on the bold line are moving averages (n=51) based on a place and the 25 smaller and larger regions. The dotted lines show a 95-percent confidence interval around the averages.

In this figure, confidence intervals, depicted by the dotted lines, are introduced to the data points shown in Figure 1. The data points show the average difference squared between location quotients and adjusted location quotients for each region in the data graphed against the region's population size. At a population size of 4,076, the lower bound of the confidence interval becomes less than or equal to zero. After this threshold, the location quotient is perfectly stable after implementing the average difference squared method.

Source: Dun & Bradstreet, County Business Patterns, American Community Survey, and authors' calculations.

Figure 3: Location Quotients have a Positive and Statistically Significant Impact on New Business Startups at Population Size Cutoff Values of up to about 5,000 Residents

This figure demonstrates how the marginal effect of region-industry location quotients changes as varying population size cutoffs are introduced. When no population cutoffs are present, the marginal effect is small (0.05) but significant. As the smallest regions are removed from the analysis, the marginal effect of the location quotient grows and remains significant. However, at a population size of about 5,000, the significance of the marginal effect becomes scattered as the sample size dwindles.

Source: Dun & Bradstreet, County Business Patterns, American Community Survey, and authors' calculations.

Figure 4: The Effect of Location Quotients on New Business Startups Switches from Inelastic to Elastic at a Population Size Cutoff of about 2,600 Residents.
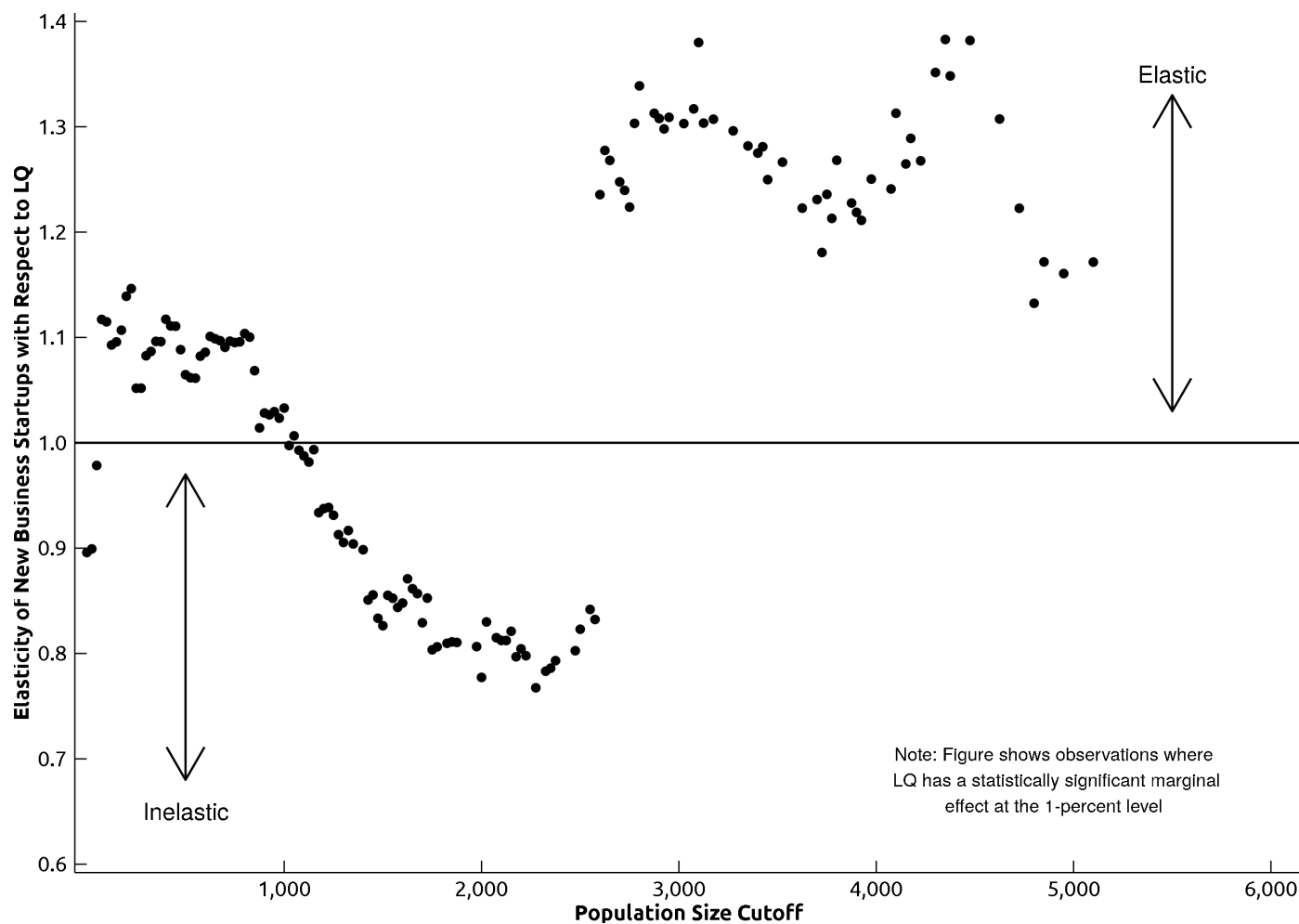
This figure shows the elasticity of new business startups, relative to the location quotient, over varying population size cutoffs. At population size cutoffs greater than 2,600, the location quotient is elastic, meaning that an increase in location quotient results in an even larger increase in number of new business startups. At population size cutoffs fewer than 2,600, on the other hand, the location quotient is inelastic for over half of the observations, indicating a weakened relationship between location quotients and new business startups.

Source: Dun & Bradstreet, County Business Patterns, American Community Survey, and authors' calculations.