# Industrial Structure and a Tradeoff Between Productivity and Resilience

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**Abstract:** The structures of regional economies play a critical role in determining both a region's productivity and its resilience to shocks. Here we extend previous work on the regional roles of occupation structure and skills structure by analyzing the effect of a region's industry structure. We operationalize the concept of economic structure by constructing a network of interdependent economic components. To measure the interdependence between economic components, we adopt the view that regional economies are analogous to ecosystems, employing techniques of co-occurrence analysis to infer interactions between industries. For each U.S. metropolitan statistical area, we then create an aggregate measure of economic tightness, capturing the degree of integration or interconnectedness among a region's industries. We find that industry tightness is positively correlated with a region's economic productivity but negatively correlated with a region's change in productivity following the Great Recession. While this result echoes prior results using occupational tightness, it differs from results using skills tightness. Thus, this study contributes to a deeper understanding of the tradeoff between productivity and resilience, and the drivers of this tradeoff. Whether regional policy makers are more focused on productivity or resilience, these insights may help guide decisions regarding which industries, occupations, or skills to emphasize in regional economic development plans. Finally, we find that regional productivity is affected by the ubiquity of the region's co-occurring industries and that regions with rarely co-occurring industries are more productive.

**Keywords:** regional science; cities; workforce; resilience; Panarchy; information theory; interdependence; co-occurrence

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## 1. Introduction

Regional economic development agencies often seek to make their cities more economically productive. Yet, simultaneously, they must address and plan for periodic shocks that disrupt regional economies, sometimes with long lasting negative impacts. Previous research has shown that these two goals may be opposed, meaning that regional planners face a tradeoff between making their cities more productive or more resilient [1]. However, it remains unclear how managers can best approach and navigate this tradeoff. What tools or models can planners employ to understand this tradeoff and which structural elements of a regional economy most influence productivity and resilience? Policy makers must further consider what economic interventions are both feasible and practical. The goal of this study is to help answer these questions and to better empower regional planners to achieve their regional development goals.

Previous studies have sought to determine the roles that both occupational structure and skill structure play in the relative productivity and resilience of U.S. regional economies. Occupational structure, in particular, was shown to strongly influence a region's vulnerability to shocks [1]. Skills structure on the other hand was shown to be more correlated with economic productivity in terms of GDP growth [2]. Here we enrich this work by analyzing a third dimension of regional economies, namely industrial structure, analyzing its impact on GDP growth, GDP per capita, response to shocks and patent production.

Prevailing conceptions of economic structure used in both academic analysis and policy decisions typically take only limited information regarding regional economic structure into consideration. For example, location quotients are frequently used as a standalone measure of regional specialization [3-5]. However, location quotients only consider proportions of individual industries relative to total employment and national shares, they do not consider inter-relations between industries or how industry groupings co-locate in various regions. Similarly, the Hirschmann-Herfindahl index is commonly used to measure regional diversity for industries but has also been applied to a wide variety of other urban phenomenon such as patenting [3,6-8]. Like location quotients, the index only examines shares and does not account for the inter-relations between industries or the co-location of industries among various sub-national regions.

Incorporating inter-industry linkages, input-output matrices measure regional economic structure by estimating flows between sectors within an economy [9,10]. However, while input-output tables can be built for various geographic scales, they do not reveal how industrial linkages locate in relation to one another among all regions in a system. For example, regional purchasing coefficients simply identify the degree to which inputs are purchased locally, there is not typically detailed examination of how likely it is for two industries that depend on one another to co-locate, thus resulting in regional purchasing coefficients [11]. A more complete examination of issues relating to the use of the input-output framework has been provided elsewhere [12].

More recently, there has been growing interest in analyzing the structure of regional economic activity more broadly. For example, international trade data has been analyzed as a bipartite network to capture the complexity of a region's economy via its trade with other regions [13]. At the sub-national level, analysis has identified that regions diversify into industries that are technological related to preexisting industries [14,15].

Advancing the literature that examines regional structure holistically, we employ a recently developed technique to operationalize and quantify such structures as networks of interdependent economic components [16]. This methodology, inspired by analyses of species co-location patterns in ecology, uses conditional probabilities to quantify the magnitude of interdependence between every pair of industries.

We then aggregate those measures of interdependence into a single measure of economic integration, or tightness, for each urban system. It is this tightness that has been previously examined with regard to regional occupation and skill structures and which we now examine in relation to industry structure. For nearly 400 U.S. Metropolitan Statistical Areas (MSAs), we determine how an MSA's level of economic tightness changed between 2001 and 2018 and how it relates to economic productivity. We then synthesize results of prior worth with current results, combining industry tightness with occupation and skills tightness to explore the possible existence of fundamental regional development pathways.

## 2. Materials and Methods

### *2.1 Data and sources*

Industry employment data is taken from a modified version of the Quarterly Census of Employment and Wages (QCEW) produced by the U.S. Bureau of Labor Statistics (BLS). The QCEW data account for all workers covered by unemployment insurance and include over 95 percent of all jobs in the U.S. This excludes unincorporated, self-employed workers. Importantly, the BLS does not publish raw QCEW data but first suppresses data that may create privacy issues if published. Because this suppression can substantially impact results, we use a modified QCEW dataset created by the Indiana Business Research Center that uses various statistical techniques to estimate and include suppressed data [17]. From this modified dataset we extract county-level industry employment data at the 4-digit North American Industrial Classification System (NAICS) code level from the annual version of the QCEW. Finally, we aggregate this county-level data to U.S. metropolitan statistical areas, which are agglomerations of one or more counties representing unified labor markets [18].

*2.2 Quantifying interdependence*

To calculate industrial tightness for all MSAs, we begin by calculating the commonly used location quotient *LQ* for each industry in each MSA:

$$LQ_{i,m} = \frac{(\, e_{i,m}/\sum_i e_{i,m})}{(\sum_m e_{i,m}/\sum_m \sum_i e_{i,m})}. \tag{1}$$

where is $e_{i,m}$ is employment in industry $i$, in MSA $m$. Thus, the *LQ* is the ratio of an industry's share of local employment to the industry's share of national employment. We use *LQ* values to create a presence-absence matrix, with industry *i* deemed present in MSA *m* if $LQ_{i,m} \geq 1$ and deemed absent otherwise.

Using this industry presence-absence matrix, we implement the methodology of [16] to calculate a measure of interdependence *x* between industries *i* and *j* as follows:

$$x_{i,j} = \frac{P[LQ_{i,m} > 1, LQ_{j,m} > 1]}{P[LQ_{i,m'} > 1]P[LQ_{j,m''} > 1]} - 1, \tag{2}$$

where *x* is the ratio of the probability that two industries *i* and *j* are both present in a randomly selected MSA, *m*, more often than they would be expected to occur individually in random cities *m′* and *m′′*. An interdependence value greater than one indicates that the two industries co-occur in cities more often than would be expected by chance and a value less than one indicates that the two industries co-occur less frequently than would be expected at random. The individual industry-pair independencies result in an industry by industry symmetric matrix.

We next use this matrix and the methodology of [1] to quantify an MSA level of industry interdependence known as tightness. We begin by weighting the sum of MSA employment in present industries by their national level interdependence as a share of total local employment:

$$L_{i,j,m} = \frac{(s_{i,m} + s_{j,m})x_{i,j}}{2\sum_i s_{i,m}} \tag{3}$$

Note that *L* is only calculated if both industries *i* and *j* are present in MSA *m*. Finally, we calculate the measure of industry tightness *T* by averaging all *L* within:

$$T_m = \frac{2}{p_m(p_m - 1)} \sum_{i<j}^{p_m} L_{i,j,m} \tag{4}$$

Thus, *T* captures the degree to which a city's economy is interdependent, integrated, or interconnected. Higher tightness indicates the presence of industry pairs that are highly interdependent with one another. Given such reliance, growth or decline in one industry may directly result from growth or decline in interdependent industries.

Finally, we standardize raw tightness values as z-scores such that the mean tightness value across MSAs = 0 and standard deviation = 1.

## 3. Results and discussion

*3.1 Industry interdependence*

For each possible pair of industries (N = 48,516) we quantified the interdependence ζ between the two industries and standardized values as z-scores. Using 2018 data we find the distribution of standardized $x$ is positively skewed (Fig. 1), ranging from range -2.96 to 17.97 with a median = -0.12 and a 90th percentile of 0.99. Industry pairs with both highest and lowest $x$ are presented in Table 1.

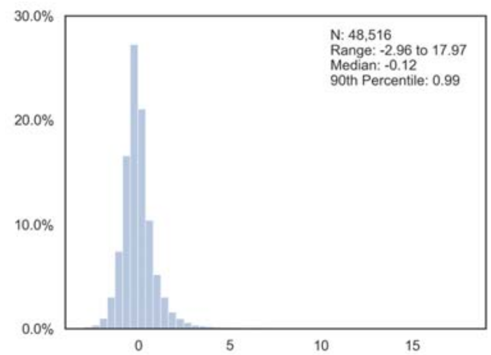


**Fig. 1. Frequency distribution of 2018 standardized industry interdependence $x$.** Although the standardized distribution of x is slightly positively skewed with a range of -2.96 to 17.97.

**Table 1. Highest and lowest standardized interdependence $x$ among U.S. industry pairs (Z-Score)**

| Rank | Industry 1 | Industry 2 | $x$ |
|---|---|---|---|
| 1 | Motion picture and video industries (5121) | Agents and managers for public figures (7114) | 17.97 |
| 2 | Monetary authorities - central bank (5211) | Securities and commodity contracts brokerage (5231) | 13.87 |
| 3 | Oil and gas extraction (2111) | Support activities for mining (2131) | 13.78 |
| 4 | Securities and commodity contracts brokerage (5231) | Other financial investment activities (5239) | 13.25 |
| 5 | Scheduled air transportation (4811) | Securities and commodity contracts brokerage (5231) | 12.95 |
| … | | | |
| 48,512 | Cut and sew apparel manufacturing (3152) | Space research and technology (9271) | -2.96 |
| 48,513 | Other support services (5619) | Space research and technology (9271) | -2.96 |
| 48,514 | Apparel knitting mills (3151) | Space research and technology (9271) | -2.96 |
| 48,515 | Textile furnishings mills (3141) | Space research and technology (9271) | -2.96 |
| 48,516 | Scenic and sightseeing transportation, other (4879) | Securities and commodity exchanges (5232) | -2.96 |

We take this interdependence matrix to be the adjacency matrix of a weighted network. In this case, nodes in the network are the 312 industries and edge values are the normalized interdependence values calculated in equation 2. We reduce the network by removing edge weights less than zero, apply the Louvain community detection (LCD), and visualize the networks using the Kamada-Kawaii algorithm in the network software Pajek [19].

Unlike similar networks created using labor skills [2,20], the network built with industries is not characterized by two polarized components or lobes. The LCD algorithm does, however, reveal two communities when using a resolution parameter of 0.5 (SOM Fig. S2). The first community is composed primarily of manufacturing and trade, transportation, and utilities, which account for 88 of the 103 nodes (85.4%) in the community (SOM Table S2). The second community is composed primarily of the remainder of industries. Manufacturing, trade, transportation, and utilities industries combined account for only 76 of the 209 nodes (36.4%) in the second community.

*MSA-level industry tightness*

Using industry-pair interdependencies we calculate an aggregate economic tightness metric of each MSA and standardize as z-scores. We find the distribution of *T* values is more highly-skewed than the underlying interdependence scores, ranging from -0.85 to 10.3, with median = -0.28 (Fig. 2). MSAs with the highest and lowest standardized tightness values for 2018 are presented in Table 2.

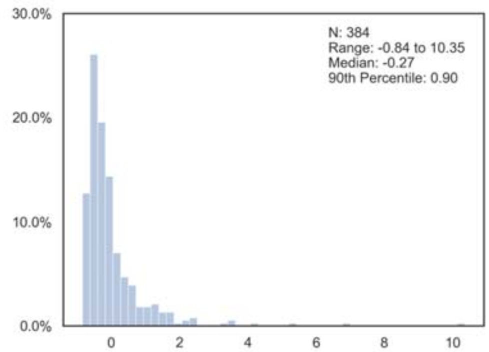


**Figure 2. Tightness z-score histogram (2018).** The distribution is more positively skewed with a maximum value of 10.35

**Table 2. Highest and lowest MSAs by 2018 standardized tightness *T***

| Rank | MSA | *T* (Z-Score) |
|---|---|---|
| 1 | San Jose-Sunnyvale-Santa Clara, CA | 10.35 |
| 2 | Midland, TX | 6.88 |
| 3 | Salinas, CA | 5.26 |
| 4 | Washington-Arlington-Alexandria, DC-VA-MD-WV | 4.15 |
| 5 | San Francisco-Oakland-Berkeley, CA | 3.47 |
| … | | |
| 380 | Elmira, NY | -0.76 |
| 381 | Kingston, NY | -0.77 |
| 382 | Manhattan, KS | -0.79 |
| 383 | Killeen-Temple, TX | -0.81 |
| 384 | Bay City, MI | -0.84 |

*Spatial distribution of T*

Analyzing the spatial distribution of *T* across MSAs (Fig. 3) we find several statistically significant clusters of MSAs with high tightness values that are not evenly distributed (Fig. 4). Using a spatial weights matrix of an MSA's 4 nearest neighbors for a local Moran's I reveals clusters of MSAs with high *T* located primarily in California. Results using other neighborhood definitions (either 2 or 3 nearest neighbors) are qualitatively similar, with additional high industrial tightness clusters centered on Washington, D.C. and Denver among others appearing (not shown).

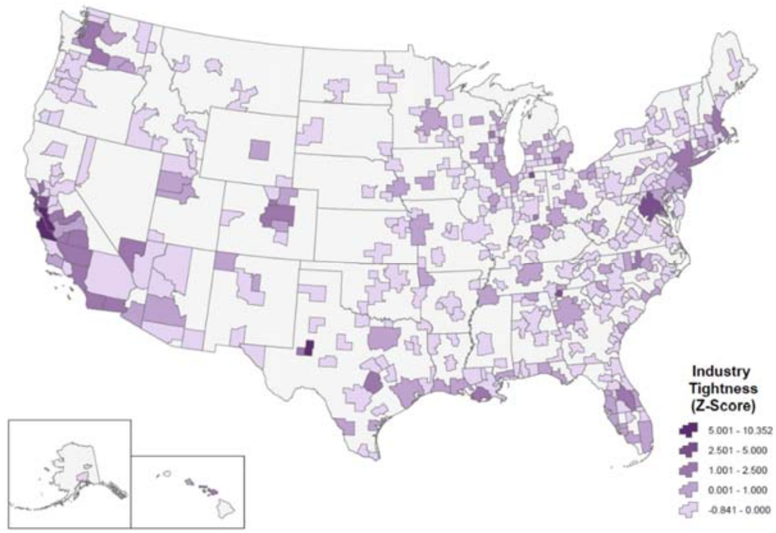


**Figure 3. MSAs by tightness z-score.** Most regions in the US have an MSA with high tightness.

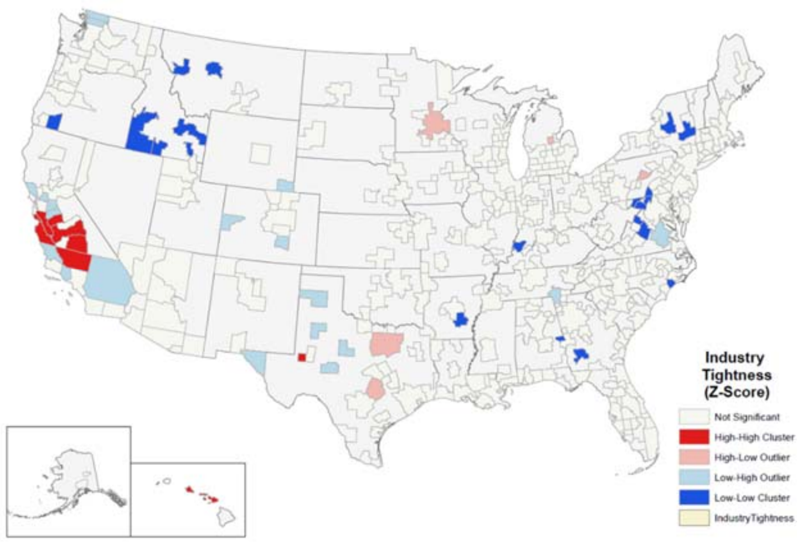


**Figure 4. LISA clusters MSA tightness z-score.** While most regions have MSAs with high tightness, California has the largest cluster of MSAs with high industrial tightness.

*Tightness over time*

The distribution of $T$ from 2001 to 2018 is displayed in Figure 5. The median normalized tightness varied from 0.25 and 0.35 over the period examined, approximately 10 percent of the normalized standard deviation of 1.0. The 95$^{th}$ percentile of the normalized tightness varied between 1.5 and 2.0 from 2001 to 2018, 50 percent of one standard deviation. The most noticeable variation occurred at the maximum, which was driven primarily by the San Francisco MSA, which had the highest tightness value for 12 of the 18 years 2001 to 2018.

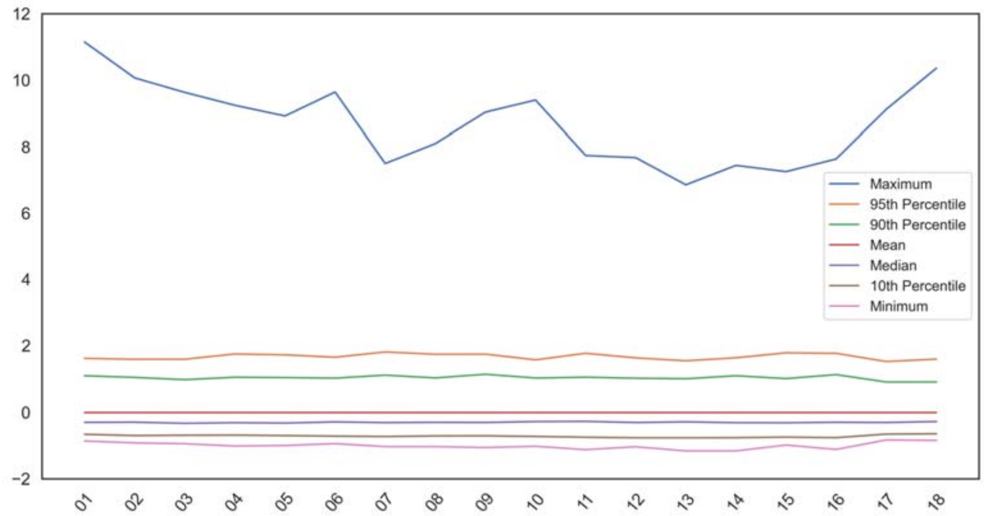


**Figure 5. Industrial tightness dispersion: 2001-2018.** The overall distribution of MSA industrial tightness remained stable from 2001 to 2018.

From a policy perspective, it is notable that the tightness of individual MSAs, particularly when ranked against all other MSAs, changes over time. For example, the rank of Hickory-Lenoir-Morganton, NC, declined from rank 8th in 2003 to 77th in 2013, while Midland, TX climbed from 22ndth in 2005 to 1st in 2014 (SOM Fig. S3). The perpetual reordering of MSAs within the overall distribution of *T* suggests that it may be possible for policymakers influence regional tightness.

*Relationship Between Tightness and Metrics of Urban Performance*

Industrial tightness correlates with multiple MSA characteristics. Industry tightness is significantly and positively correlated with GDP per capita (adj $R^2 = 0.43$, $p < 0.001$) (

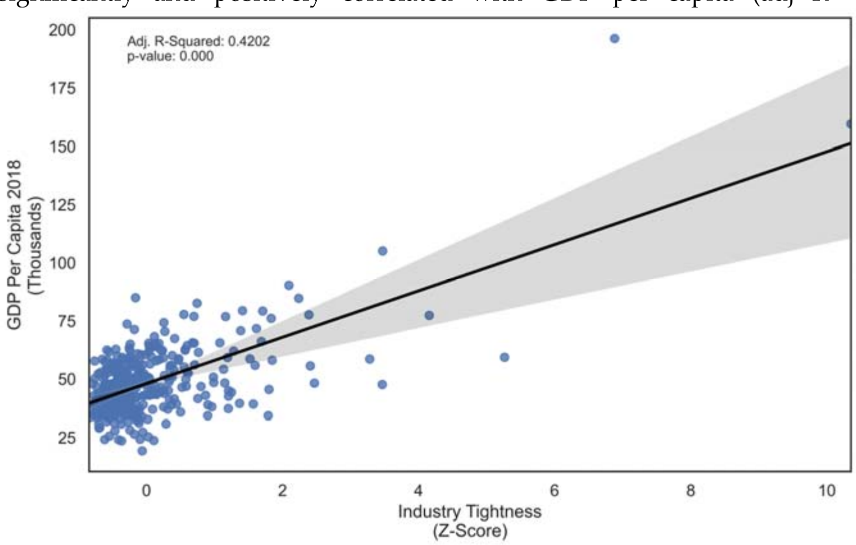


Figure **6**). A one standard deviation increase in industrial tightness is correlated with an increase in GDP per capita of $9,971. Industry tightness is also significantly and positively correlated with growth in GDP per capita (

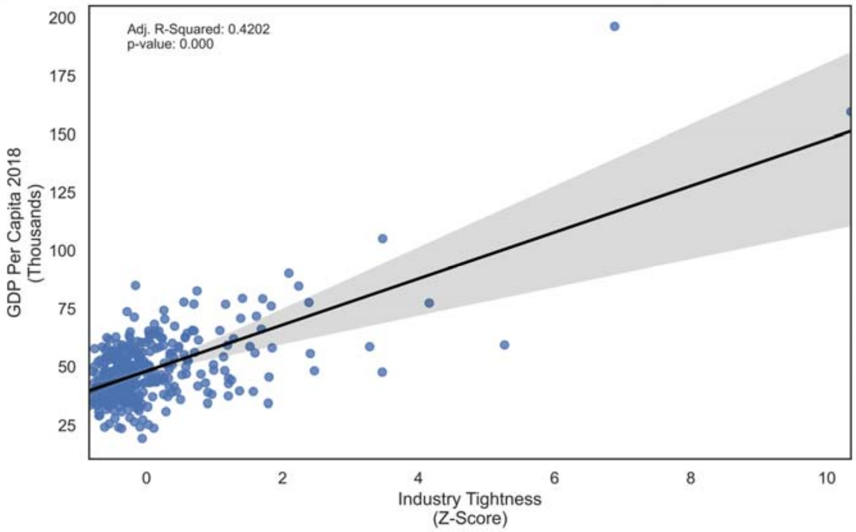


Figure **6**).

To examine the relationship between industry tightness and economic vulnerability, we use data covering the period of the 2007-2009 global recession. We regress the percent change in MSA GDP per capita from 2006 to 2009 on 2006 MSA tightness (see SOM). Unlike occupational tightness [1], we find no statistically significant correlation between industry tightness and change in an MSA's per capita GDP during the recession. Two additional variables examined are the logarithm of MSA population and patents per worker (Table 3). While MSA industrial tightness is significantly correlated with both population and patents per worker, both also have low explanatory power.

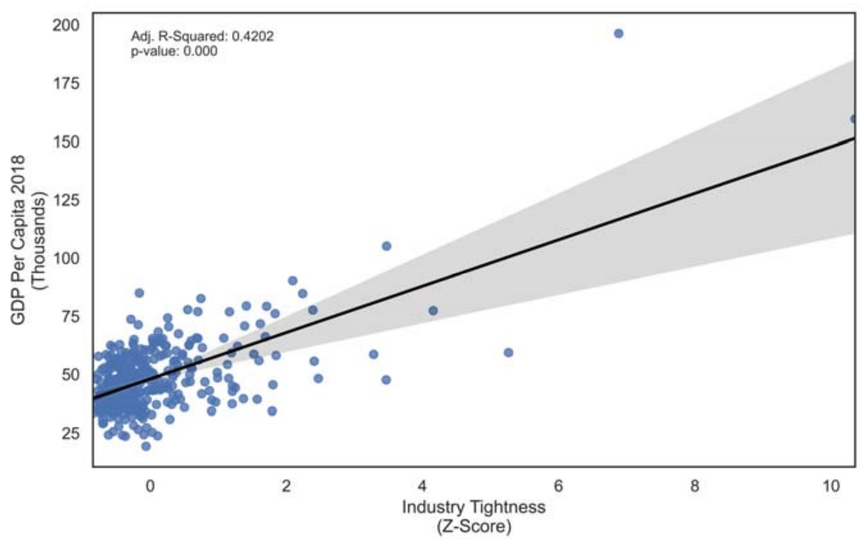


**Figure 6. Industrial tightness vs. GDP per capita (thousands of $).** MSA industrial tightness is positively correlated with regional economic productivity.

**Table 3. Tightness versus metrics of urban performance**

Single Variable Regression of Industrial Tightness versus:

| | GDP Per Capita (Thousands) | GDP Per Capita Change 2015 – 2018‡ | Log Population | Patents Per 1,000 Workers (2015) |
|---|---|---|---|---|
| Const. | 47.97 | 0.04 | -3.29 | 0.68 |
| Beta | 9.97*** | 0.014*** | 0.26*** | 0.41*** |
| (SE) | (0.597) | (0.002) | (0.045) | (0.056) |
| Adj. R2 | 0.42 | 0.094 | 0.079 | 0.122 |
| N | 384 | 384 | 384 | 375 |

Note: Patent data are sourced from the USPTO

*** significant at the 1% level.

‡ Dependent tightness data are 2015 Industrial Tightness, 2015 OMB MSA definitions.

The close positive correlation between industrial tightness and productivity raises natural questions as to the source of the correlation. Regarding time dynamics, there are at least two plausible explanations of how the correlation between MSA industrial tightness and GDP per capita could developed within any individual MSA. First, productivity could lead to greater industrial tightness as greater competition for resources results in an exclusionary process that drives non-related, less productive, industries out of the regional market either through relocation or closure. Such a dynamic process has been identified in regional economies resulting from firm formation [21]. Second, industrial tightness could induce all economic activity to become more productive, without exclusionary processes, as the complex interactions of the tightly bound economy find additional productive uses for existing industries. If complex inter-industry linkages induce regional economic productivity without an exclusionary process, the concern among ecologists that strong asymmetric relationships resulting in one species excluding another, and thus the relationship going unmeasured, would be diminished for regional economic analysis [22]. Examining the exclusionary processes that may be at work seem a fruitful area of future research.

There are additional considerations that may play a role in the strong correlation between industrial tightness and productivity. For example, the overall correlation results from a small number of rarely co-occurring industry-pairs. The overall correlation could also result from the diversity of co-occurring industry pairs. While there are numerous plausible explanations, we analyze the possibility that the correlation is driven by rarely co-occurring industry-pairs.

Rareness of industry co-occurrence could be quantified several ways. For instance, the individual occurrences of two industries could be independently rare, making a co-occurrence of both industries highly unlikely. It could also be the case that two industries have a low $x$, meaning that while they both may occur independently in many MSAs, they rarely co-occur. A parsimonious measure of industry-pair rarity is a simple count of the number of MSAs in which industry pair *i,j* co-occurs. More formally:

$$c_{i,j} = \sum_{m} p_{i,j,m} \tag{5}$$

where

$$p_{i,j,m} = \begin{cases} 1 \ \text{ if } LQ_{i,m} > 1, \quad LQ_{j,m} > 1 \\ \quad 0 \ \ Elsewhere \end{cases} \tag{6}$$

We calculate $c$ for each of the 48,451 unique industry pairs that co-occur at least once (65 industry pairs never co-occur). The distribution of $c$ is highly skewed, with a median of 26, an average of 31.9 and a maximum of 255 (Fig. 7).

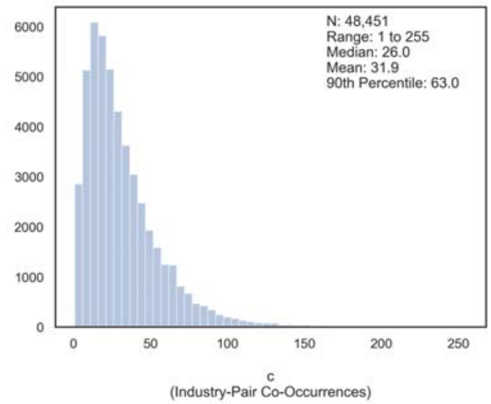


**Figure 7. Histogram of industry-pair co-occurrences.** The distribution of the number of co-occurrences is highly skewed, the median number of co-occurrences is 26 MSAs.

Industry-pairs with high interdependence values co-occur more rarely than industry-pairs with lower interdependence values (SOM Fig. S4). In order to have a high inter-dependence values, two industries have to both be specialized in only a few places and co-occur in more places than would be expected by random chance. If two industries co-occur far more frequently than would be anticipated by random chance, it is likely the case then that they are more productive together than they are separately, thus capturing the essence of the measure, and resulting in the tight correlation between tightness and economic productivity.

To determine how $c$ varies with city characteristics, we first plot $c_{i,j}$ against the average MSA population where $p_{i,j,m} = 1$ (Fig. 8). Given that the data are not normally distributed and heteroskedastic, we report the mean of the average city-size for each $c$. Rarely occurring industry-pairs are more likely to co-occur in larger MSAs. The mean average city-size in which an industry-pair co-occurs rises from 2.38 million when $c = 1$ to 2.6 million when $c = 5$. From this peak the mean average city-size in which an industry-pair co-occurs falls to 1.06 million when $c = 30$.

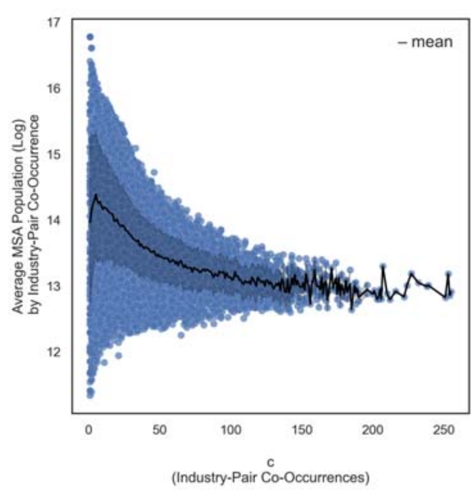


**Figure 8. Average MSA population (log) vs. number of industry-pair co-occurrences.** Industries that rarely co-occur typically co-occur in larger MSAs.

Plotting the average GDP per capita where $p_{i,j,m} = 1$ against $c_{i,j}$ reveals a similar relationship (Fig. 9). Rarely occurring industry-pairs are more likely to occur in MSAs with higher GDP per capita. The mean average GDP per capita of MSAs in which an industry-pair co-occurs declines from $58,664 when $c = 1$ to $49,972 when $c$ = the median of 26. As $c$ increases, the mean average GDP per capita across MSAs asymptotically approaches approximately $43,000.

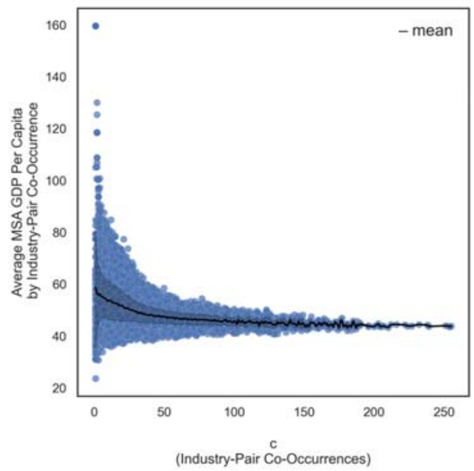


**Figure 9. Average MSA per capita GDP vs. number of industry-pair co-occurrences.** Industries that rarely co-occur typically co-occur in more productive MSAs.

Given that the mean average per capita GDP declines as $c$ increases suggests that cities with rarely co-occurring industry-pairs have higher per capita economic output. To examine this further, we compare the average $c$ for industry-pairs that co-occur in an MSA to the MSA's per capita GDP (Fig. 10). The correlation between the average $c$ of industry-pairs that co-occur within the MSA and the MSA's per capita GDP is negative and significant (adj R2 = 0.27, $p < 0.001$). Regions with industries that rarely co-occur are more productive than regions with more ubiquitously co-occurring industries, providing further evidence that the co-occurrence measure underlying the MSA-level tightness measure captures inter-industry productivity benefits not captured when using traditional tools, such as location quotients, alone.

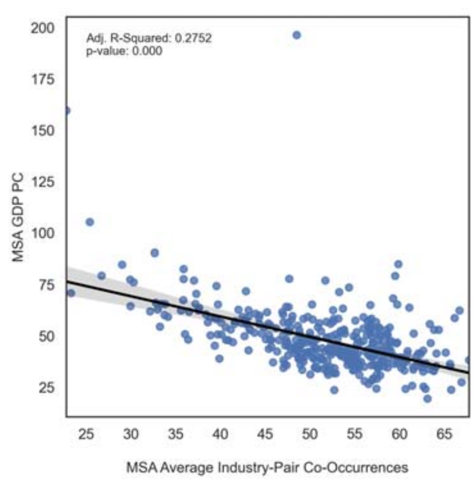


**Figure 10. MSA industry-pairs average co-occurrence vs. per capita GDP.** MSAs with rarer industry pairs are more productive.

*Industries, occupations, and skills – synthesizing past work on economic structures*

Finally, we synthesize the results of this study, using tightness based on industries, with previous work using tightness based on occupations [1] and on skills [2]. Comparing industrial tightness to both occupational tightness and skills tightness reveals that the industrial tightness is linearly correlated with occupational tightness while the relationship with skills tightness is non-linear (**Error! Reference source not found.** SOM Figs. S6-S8). The linear correlation between industrial tightness and occupational tightness is positive and significant (adj. $R^2 = 0.65$, $p < 0.001$). Thus, while industrial and occupational tightness appear to be closely related, skills tightness stands out as distinct from the other two measures.

**Table 4. Industry tightness versus occupation and skills tightness**

| | Single Variable Regression of Industrial Tightness (Z-Score) vs.: | |
|---|---|---|
| | **Occupational Tightness** | **Skills Tightness** |
| Const. | 0.01 | 0.04 |
| Beta | 0.811*** | 0.301*** |
| (SE) | (0.031) | (0.048) |
| Adj. R2 | 0.646 | 0.094 |
| N | 365 | 365 |

* significant at the 1% level.

Integrating this study with previous work, a summary of the various metrics of tightness and their relationships with economic indicators is presented in Table 5. Overall, we find that all measures of tightness are positively and significantly correlated with economic performance in the absence of shocks. However, following a shock both higher occupation and industry tightness are correlated with higher percentage drops in economic performance. On the other hand, higher skills tightness is correlated with increased economic performance following a shock.

**Table 5. Correlation between various measures of economic tightness and economic performance metrics**

| | Tightness based on: | | |
|---|---|---|---|
| | **Occupations** | **Skills** | **Industries** |
| Per capita GDP | + | + | + |
| Per capita personal income | + | + | + |
| Change in per capita GDP, following shock | − | + | − |
| Change in per capita personal income, following shock | − | n.s. | − |

n.s. = not significant

The implications of this summary for policy makers is that there exists a tradeoff between economic productivity and economic resilience. Attracting industries and jobs that increase tightness may enhance economic efficiency but at the cost of resilience in the event of a shock. However, to the extent that policy makers can promote higher skills tightness without increasing occupational or industrial tightness may simultaneously enhance both productivity and resilience. However, it remains unclear what policy options might influence only specific components of a regional economy and further research is required to determine realistic policy options that best empower policy makers to navigate the productivity-resilience tradeoff.

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**Data Availability:** All data used in this study will be made available upon request to the authors.

**Supplement Online Materials:** Included with this pdf file.

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