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Article

Innovations and Economic Output Scale with Social Interactions in the Workforce

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Abstract: The COVID-19 pandemic of 2020 changed the way we interact and engage in commerce at a fundamental level. Social distancing and stay-at-home orders leave businesses and cities wondering what economic activity will look like in the future. Given a likely reduction in face-to-face interactions, it is important to better understand how social interactivity influences economic outcomes. Here we measure the effect of social interactions in the workforce on patent production and economic efficiency. We decompose U.S. occupations into individual work activities, determine which of those activities are associated with face-to-face interactions, and reaggregate the labor force of each U.S. metropolitan statistical area (MSA) into a metric of social interactiveness. We then calculate each MSA's density of social work activities and find that this measure is more highly correlated with an MSA's per capita patent production than simple population density. This suggests that density of face-to-face interactions is the important driver of a city's rate of invention. We close by exploring analogies between the development of cities and the development of stars, suggesting ways these analogies may help frame future research on cities.

Keywords: Innovation; Sociality; Economic Impact; Labor Dynamics; Urban Density

1. Introduction

The way employees interact with each other in the workplace and with consumers shifted dramatically in 2020 due to the COVID-19 pandemic [1–3]. Social distancing and stay-at-home orders have led to more people working from home and ordering more goods online than ever before [4,5]. This leaves businesses and cities scrambling to define and adapt to the "new normal" [6,7]. How do these changes in labor affect an industry's profitability per worker [8–10]? How can cities continue innovating during a time of social transition [11–13]? The first steps to creating a plan forward is understanding the role social interactions play in the workplace and within the city as a whole. This study explores how gross domestic product (GDP) per worker and per capita patent production are affected by face-to-face interactions of workers.

Innovation is generally accepted to be a desirable attribute of societies. It drives the emergence of novel technologies, products, and processes that tend to enhance the collective well-being of human populations. Innovation has tended to concentrate in cities, particularly larger cities, and previous research has shown a strong superlinearly relationship between innovation and city size [14,15]. Similar superlinear scaling has been revealed for economic opportunity [16,17] and several other urban indicators related to innovation and technology [18].

While these studies demonstrate a strong relationship between aggregate patent output and city size, we are instead interested in what drives the *rate* of innovation,

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measured as a city's patent output per capita. We believe a key driver of this metric is not population but population density. Yet, it is not simply density of people that is critical to fostering innovation, but a phenomenon largely omitted from previous research, namely the density of social interactions.

More precisely we ask, why do some cities develop into innovation engines, while others grow into merely areas of highly dense population? We hypothesize that these divergent pathways are a results of the density of some intangible quality of "socialness". Such socialness is particularly important among businesses, where innovation is shown to be enhanced by face-to-face interactions between workers and clients [19,20] and by collaboration between individuals [21]. Thus, we quantify a city's density of socialness by measuring the density of workers in occupations that require some degree of social interaction.

We use the O*NET data set, which decomposes U.S. occupations into a series of attributes, each of which we classify as either social or not. Applying those attributes to the occupational distribution of a city's labor force, we create an aggregate metric of the socialness of each city's workforce. We combine this metric with a novel measure of a city's effective urban area to calculate a city's density of social interactions. We then correlate cities' densities of socialness with their rates of patent production. To further investigate the importance of worker socialness, we analyze its effect on industry productivity by correlating the worker socialness of individual industries with the per worker GDP of those industries.

2. Materials and Methods

2.1. Defining our cities

Our geographical units of analysis are U.S. metropolitan statistical areas (MSAs). MSAs are aggregations of one or more counties, have a combined population of at least 50,000, and exhibit a high degree of economic cohesion as measured through commuting patterns [22]. Our set of 395 MSAs is taken from the 2018 Occupational Employment Statistics published by the U.S. Bureau of Labor Statistics [23].

2.2. Measuring socialness of a city

We use two approaches to measuring the socialness of city's labor force. In each case we use the O*NET data set of occupational attributes [24] to assess the intensity of social interactions that occur while performing one's job. Note that this does not attempt to capture social interactions that occur during non-work activities, e.g. during leisure time.

In method one, we utilize O*NET data on an occupation's individual work activities (IWAs.) O*NET recognizes 332 IWAs that are present or not in an occupation. We designate each IWA as either social or non-social depending on whether the activity typically requires face-to-face interactions with another person. For instance, we categorize the IWA "Coordinate with others to resolve problems" as social and the IWA "Assemble equipment or components" as non-social, (see Table 1 for more examples and the supplementary materials for the full list.) Thus, for each occupation we develop a vector of social activities. We then calculate the degree to which an occupation is socially interactive by summing the number of social activities associated with that occupation. Finally we multiply an occupation's number of social IWAs by the number of workers in that occupation in each MSA to obtain an aggregate measure of socialness by MSAs.

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Table 1. Classification of example individual work activities (IWAs). See supplemental materials for complete list.

Individual Work Activity (IWA)	Sociality
Explain technical details of products or services	social
Promote products, services, or programs	social
Monitor environmental conditions	non-social
Diagnose health conditions or disorders	social
Test characteristics of materials or products	non-social
Prepare medical equipment or work areas for use	non-social

In method two, we use the previous calculation of the number of social IWAs per occupation. However, we apply a threshold of social IWAs to determine whether an occupation is a social occupation or not. We then apply that designation to an MSA's occupational workforce census to capture the total number of social workers in the city's workforce, which we take as the second aggregate measure of an MSA's socialness. In this study, we take an occupation with 9 or more social IWAs to be a social occupation and we take the workers in those occupations for each MSA to be the MSA's social workers.

Having determined the socialness of each occupation, we then apply that determination to each MSA's employment distribution by occupation. We take these distributions from the Occupational Employment Statistics (OES) dataset published annually by the U.S. Bureau of Labor Statistics. Here we use the May 2018 edition of the OES [23].

2.3. Density of social interactivity by city

To estimate the density of our cities, we use two determinations of MSA area, an MSA's total area and an MSA's effective urban area. To determine the latter, we adopt the view that an MSA's effective urban area is the portion covered by impervious surfaces, such as roads, parking lots, buildings, and other hard infrastructure [25]. Data for each MSA's area of impervious surface was extracted from the 2016 U.S. National Land Cover Database (NCLD) [26], using the dataset on Imperviousness for the continuous U.S. from all years. Thus, our measure of effective urban area excludes undeveloped areas within MSA boundaries. We then divide our measures of social workers by both values of area to calculate our metrics of an MSA's density of worker socialness.

2.4. Innovation rates

As a proxy for rates of innovation we use rates of patenting by MSA. Because patent output varies considerably from year to year, we sum each MSA's total patent output from 2011 – 2015, which are the most recent 5 years available from the U.S. Patent office [27]. We then divide those totals by number of workers in an MSA to derive the MSA's patenting rate.

2.5. Industry socialness and productivity

Similar to our method of determining a city's socialness, we apply the social characteristics of occupations to the occupational distributions of industries instead of MSAs. Similar to occupational distributions for MSAs, the occupational distributions for industries are included in the Bureau of Labor Statistics' OES dataset. However, they are taken not from the area distributions but from the OES's industry tables [28].

To understand how worker socialness affects productivity we compare an industry's socialness to each industry's productivity, measured here as per worker GDP. Per worker GDP numbers are taken from the U.S. Bureau of Economic Analysis, which publishes annual estimates of both employment and aggregate value added by industry [29].

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3. Results and Discussion

3.1. Rates of Patent Production and Workforce Socialness

Patent production has previously been used as a proxy for innovation and has been shown to scale superlinearly with city size [14,18,30]. Another way to interpret this superlinear scaling is that the amount of patents per person increases with city size. In [14,18,30], they did not attempt to explain in detail why the rate of patenting increases with city size, but pointed out that patenting was part of a larger group of urban attributes that scale superlinearly, most related to technology and innovation. While this finding is objectively interesting and useful, it is limiting in its applications for city officials interested in increasing their city's innovation output. It is of little use to officials trying to create more innovation within their city if the recommendation is simply to make the city bigger. Increasing city population is not always feasible in the short-term and fails to make the city more efficient.

While previous studies found that per capita patent production scaled with city population [14,18], our goal is to offer a deeper explanation of the drivers of the rate of patenting, as a proxy for the rate of innovation. Therefore, we focus on patents per worker as our dependent variable. We choose to focus on the rate at which patents are produced per worker instead of aggregate patent output because aggregate rates can produce misleading results during innovation booms [31,32].

We first determine the correlation between patenting rates and two measures of city size – total employment and geographic area. As expected, correlations are low. We instead expected innovation rates to be related more to density than size. This is indeed the case when comparing patent rates to simple worker density, with $R = 0.26$ when density was based on total area and $R = 0.38$ when density was based on urbanized area. However, we hypothesize that it is not simply worker density, but density of socially interactive workers that is the key driver of higher rates of innovation. Thus, we examine the relationship between patent rates and two measures of social worker density, finding in both cases that R increases substantially using either total area or urbanized area to calculate density. Correlation coefficients for the various attributes we examined are given in Table 2.

Overall, we find the highest correlation with patents per worker is with density of social workers, where density is based on urbanized area. This is an improvement in R of 0.14 compared to the correlation with density of all workers. We find this result reasonable as there is substantial literature about increased production of innovation and collaboration [33–39]. To summarize, the number of innovations produced increases with collaborations between groups of individuals up to a point of diminishing returns. In general, innovations are more likely to occur when diverse individuals are able to brainstorm and bounce ideas off each other.

Results suggest an intriguing pathway by which policy makers might increase rates of patent production, namely by increasing socialness of its workforce. This might be accomplished, for instance, by attracting industries with a high proportion of social workers or by implementing mechanisms that increase the likelihood of interactions among social workers.

Table 2. Correlation coefficients (R) of MSA patenting rates versus workforce characteristics using two definitions of MSA area.

Patents per worker vs.	Total Area	Urbanized Area
Size - Total employment	0.10	n/a
Size - Area	-0.03	0.04
Density - all workers	0.26	0.38
Density - social IWAs	0.31	0.46
Density - social workers	0.37	0.52

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3.2. *Worker Socialness and Economic Productivity*

In addition to patent rates, we find a significant relationship between per worker GDP and the number of social activities per worker. We find that this relationships takes the form of a power law

$$y = \alpha x^{\beta}, \tag{1}$$

where y = GDP per industry worker, x = the average number of social tasks per industry worker, α is the normalization constant, and β is the scaling coefficient. Here our units of analysis are specific industries instead of MSAs. Plotted in log-log space for approximately 100 industries, Figure 1 illustrates the power-law relationship between these variables, with $\beta = 1.46$. The superlinear scaling of this relationship indicates a feedback loop in which increasing numbers of social activities performed by workers is associated with exponential growth of GDP per employee. Taking GDP per worker as a measure of an industry's economic productivity, companies desiring enhanced productivity may seek ways to increase the number of social activities of its employees.

GDP vs socialness.PDF

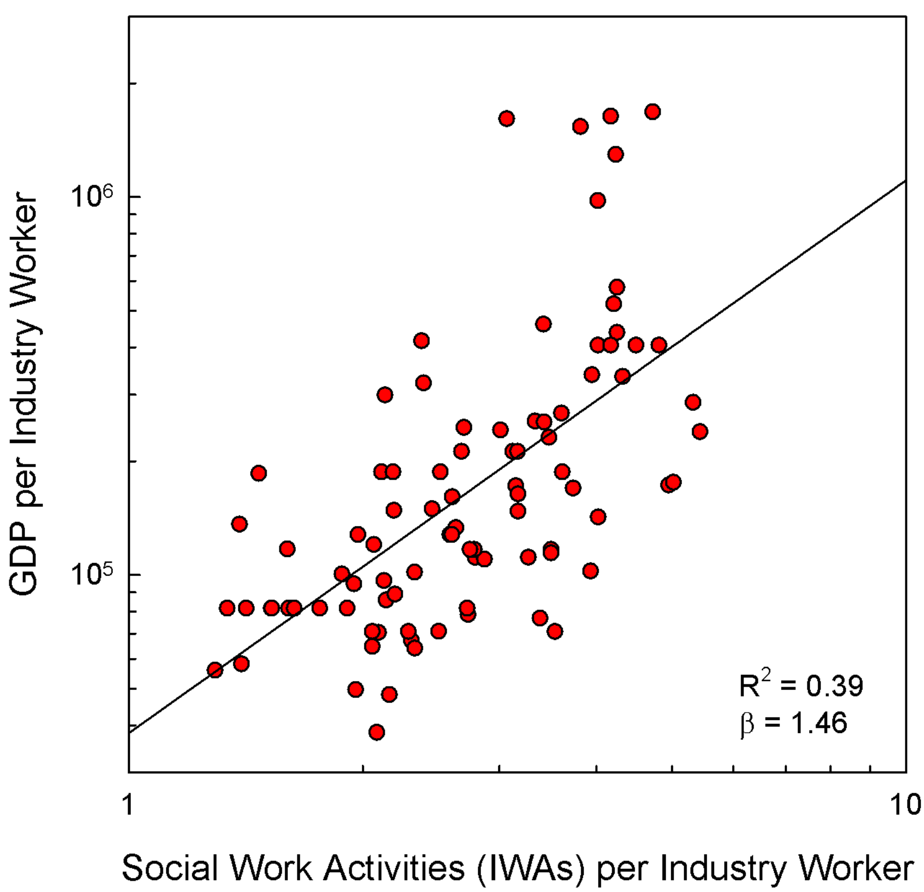

Figure 1. Power-law relationship between GDP and socialness. Both axes are logarithmic. Each dot represents an individual industry for which 2018 GDP and employment data is available (N = 102). As the number of social work activities per worker increases, GDP per worker increases superlinearly.

This result echoes the result of our patent rate analysis. If a city's workforce is more social, it generally produces more patents–more innovations–per worker than cities with a less social workforce. If an industry's workforce is more social, that industry generates higher GDP per worker than industries with a less social workforce. While many studies measure GDP per employee [40–43], none to our knowledge has considered the effect

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that worker socialness has on per employee GDP. One might then infer worker socialness could also be a key to enhancing a city's per capita GDP. While several studies examine the relationship between industry, their resident cities, and the industry's effect on GDP [44–46], none have considered the effect of the density of social activities per worker. While this result points to promising pathway for increasing worker productivity, further research on how worker socialness affects economic output is needed to confirm this finding.

3.3. Intriguing analogies between cities and stars

In previous research it has proved useful to create biological metaphors of cities as "living systems" [47] often having a "metabolism" [48]. While biological metaphors have proven useful historically [49], there is a history of using purely physical systems as metaphors for the biological. Some of the earliest metaphors used tubes to explain the circulatory system [50]; later, it was the body as a machine [51] or the brain as a computer [52].

However, in interpreting our results we are struck by a novel analogy of cities as a physical system rather than a biological system. In particular we note that the phenomena we examine among urban systems have intriguing analogies with the evolution of stars. Similar to the critical role of social interactions between humans in the process of innovation [19,20], the rate at which hydrogen atoms interact in stellar gas clouds plays a critical role in whether the cloud will ignite into a radiant start or collapse into a dense, but dark, degenerate star. Stellar dust clouds with sufficient density, but without the requisite temperature, will fail to ignite. Similarly, cities require a critical combination of both population density and social interactions before they can "ignite" to become innovation engines [53,54]. This analogy becomes especially compelling given that temperature is related to how frequently and energetically that atoms in a stellar cloud collide. The analogy applies also to rates of industry productivity, as we find that industry per capita GDP is positively correlated with worker socialness.

Thus, our findings suggest that increasing the density of social activity–whether by increasing the density of social workers in a city or by increasing the number of social activities per industry worker–is likely to increase urban innovative output or GDP per employee.

Stellar analogies apply also to other aspects of urban development. One example we highlight as a future research direction is the analogy between a star's evolution and urban gentrification. Gentrification proceeds through predictable stages, each with characteristic wages, housing costs, industries, infrastructure, and population demographics [55,56]. Both housing costs and per capita wealth tend to increase in neighborhoods passing through stages of gentrification. Similarly stars pass through predictable stages of fuel consumption, first fusing hydrogen into helium, then fusing helium into oxygen, and so on through stages that create increasingly heavier elements. Eventually stars may reach the stage of iron production, which is too heavy to be further consumed. Unable to continue the fusion of heavier elements, a star's internal structure becomes unsustainable and the star typically collapses and explodes. Thus, there is a potential lesson in this analogy for gentrifying neighborhoods - that gentrification may have a limit at which increasing housing costs and wealth requirements become unsustainable leading to collapse, for example, into a ghost town or slum [57]. One might even take the stellar metaphor a step further by invoking red dwarf stars which burn their fuel at a slower rate extending their lifespan dramatically [58]. This might suggest that policy makers utilize available resources at a measured pace to ensure sustainable growth. Again, further exploration of this example would be an interesting application of this stellar metaphor of urban development.

4. Conclusions

This study identifies a power law relationship between socialness and both industry GDP per worker and urban per capita patent production. Furthermore, we briefly introduce the potential utility of analogies between cities and stars, particularly in considering how density of social interactions can "ignite" a city or industry.

Finally, we return to the implications of these findings given the ongoing COVID-19 pandemic. While social distancing mandates, stay-at-home orders, and compulsory face mask use are being widely implemented to slow the spread of COVID-19, these policies come at a cost of social interactions. Invoking our stellar metaphor, COVID-19 has effectively decreased the temperature in urban cores. This leads to new questions including how this reduced socialness will affect innovation of cities and industries and whether policy interventions can be crafted that both maintain levels of social interaction and keep citizens safe. In particular, the unique risks that high density cities encounter when attempting to create healthy spaces during this pandemic [59]. We believe a stellar model may help better address these and related questions about recovery after the pandemic.

Supplementary Materials: The following are available at https://www.mdpi.com//1/1/0/s1, Figure S1: title, Table S1: title, Video S1: title. A supporting video article is available at doi: link.

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