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Innovations and Economic Output Scale with Social Interactions in the Workforce

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Abstract: The COVID-19 pandemic of 2020 fundamentally changed the way we interact with and engage in commerce. Social distancing and stay-at-home orders leave businesses and cities wondering how future economic activity moves forward. The reduction in face-to-face interactions creates an impetus to understand how social interactivity influences economic efficiency and rates of innovation. Here, we create a measure of the degree to which a workforce engages in social interactions, analyzing its relationships to economic innovation and efficiency. We do this by decomposing U.S. occupations into individual work activities, determining which of those activities are associated with face-to-face interactions. We then re-aggregate the labor forces of U.S. metropolitan statistical areas (MSA) into a metric of urban social interactiveness. Using a novel measure of urbanized area, we then calculate each MSA's density of social work activities. We find that our metric of urban socialness is positively correlated with a city's per worker patent production. Furthermore, we use our set of social work activities to reaggregate the workforces of U.S. industries into a metric of industry social interactiveness, finding that this measure scales superlinearly with an industry's per worker GDP. Together, the results suggest that social interaction among workers is an important driver of both a city's rate of invention and an industry's economic efficiency. Finally, we briefly highlight analogies between cities and stars and discuss their potential to guide further research, vis-à-vis the density of social interactions "igniting" a city or industry.

Keywords: innovation; sociality; economic impact; labor dynamics; urban density; COVID-19



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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 [8–11]? How can cities continue innovating during a time of social transition [12–14]? The first step to creating a plan forward is understanding the role social interactions play in the workplace and within the city as a whole. In this study, we examine how gross domestic product (GDP) per worker and patent production per worker are affected by face-to-face interactions in the workforce.

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 superlinear relationship between innovation and city size [15,16]. Similar superlinear scaling has been revealed for economic opportunity [17,18] and several other urban indicators related to innovation and technology [19].

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, measured as a city's yearly patent output per worker. We believe a key driver of this metric is not workforce size but worker density. Yet, it is not simply density of workers 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 result 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 [20,21] and by collaboration between individuals [22]. 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 [23]. Our set of 395 MSAs is taken from the 2018 Occupational Employment Statistics published by the U.S. Bureau of Labor Statistics [24].

2.2. Measuring Socialness of a City

We use two approaches to measure the socialness of a city's labor force. In each case, we use the O*NET data set of occupational attributes [25] 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). For each IWA, we let $A_s = 1$ if it is a social activity and $A_s = 0$ otherwise. Thus, for each occupation o , we take its socialness to be the total number of social work activities present in o

$$S_o = \sum A_s \quad (1)$$

where S_o is the socialness of occupation o . We then multiply S_o by the number of workers in occupation o in each MSA m and sum across all occupations in m to obtain an aggregate measure of socialness by MSA,

$$S_m = \sum_{o=1}^{N_m} S_o w_{o,m} \quad (2)$$

where N_m is the number of occupations with employment in MSA m , $w_{o,m}$ is the number of workers in occupation o in m , and S_m is the socialness of the workforce in m . We take

the distribution of workers in each occupation in each MSA $w_{o,m}$ 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 [24].

Table 1. Classification of example individual work activities (IWAs). See Supplementary Materials for a 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 S_o (Equation (1)). We then apply a threshold number of social IWAs to determine whether occupation o is a social occupation or not. In this study, we take an occupation to be social if it has nine or more social IWAs

$$S'_o = \begin{cases} 1 & \text{if } S_o \geq 9 \text{ (social)} \\ 0 & \text{otherwise (non-social).} \end{cases} \quad (3)$$

We then modify Equation (2) to derive an alternative measure of the worker socialness of MSA m ,

$$S'_m = \sum_{o=1}^{N_m} S'_o w_{o,m}. \quad (4)$$

Thus, while S_m is the aggregate number of social worker activities carried out in m , S'_m is the aggregate number of workers engaged in social occupations in m .

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 [26]. Data for each MSA's area of impervious surface were extracted from the 2016 U.S. National Land Cover Database (NCLD) [27], 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 workers socialness by both values of area to determine an MSA's density of worker socialness; formally the density of social work activities is

$$D_m = \frac{S_m}{a_m} \quad (5)$$

and the density of social workers is

$$D'_m = \frac{S'_m}{a_m} \quad (6)$$

where a_m is the area of m and can be measured either as total area or effective urban area.

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, for each MSA m , we sum total patent output p_m from 2011–2015, which are the most recent 5 years available from the U.S. Patent

Office [28]. We then divide those totals by total workforce of m to derive an MSA's per capita patenting rate:

$$P_m = \frac{p_m}{w_m} \quad (7)$$

where w_m is the total number of workers in MSA m .

2.5. Industry Socialness and Productivity

To understand how worker socialness affects productivity, we analyze industries instead of MSAs. We first calculate an aggregate measure of socialness for each industry i by modifying Equation (2) as

$$S_i = \sum_{o=1}^{N_i} S_o w_{o,i}, \quad (8)$$

where N_i is the number of occupations having workers nationally in industry i and $w_{o,i}$ is the number of workers nationally in occupation o in industry i . We take these occupational employment distributions by industry from the BLS's OES industry tables [29] as opposed to the OES area tables used in Equation (2). We then divide an industry's aggregate socialness S_i by the total number of employees nationally in industry i to get an average worker socialness by industry x_i .

We then compare that industry average to each industry's productivity, measured here as an industry's average per worker GDP y_i . Per worker GDP numbers are calculated using U.S. Bureau of Economic Analysis annual estimates for both employment and aggregate value added by industry [30]. We model the relationship between industry socialness and economic productivity as the power law function

$$y_i = \alpha x_i^\beta, \quad (9)$$

where y_i = average GDP per worker in industry i , x_i = average number of social tasks per worker in industry i , α is the normalization constant, and β is the scaling coefficient.

3. Results and Discussion

3.1. Rates of Patent Production and MSA Workforce Socialness

Patent production has previously been used as a proxy for innovation and has been shown to scale superlinearly with city size [15,19,31]. Another way to interpret this super-linear scaling is that the amount of patents per person increases with city size. In [15,19,31], the authors 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 increase innovation within their city if the solution is simply to make the city bigger.

While previous studies found that per capita patent production scaled with city population [15,19], 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 [32,33].

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 the level of effective 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 regarding the relationship between innovation and collaboration [34–40]. This literature asserts that 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 share ideas.

The 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. Using effective urbanized area gives consistently larger R values.

Patents per Worker (P_m) vs.	Total Area	Urbanized Area
Size: total employment (w_m)	0.10	n/a
Size: area (a_m)	−0.03	0.04
Density: all workers (w_m/a_m)	0.26	0.38
Density: social IWAs (D_m)	0.31	0.46
Density: social workers (D'_m)	0.37	0.52

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. Here, instead of MSAs used in the rate of patent production calculations, our units of analysis are industries for which occupational distributions are included in the Bureau of Labor Statistics' OES dataset [24]. 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 are 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 might seek ways to increase the number of social activities of its employees.

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 [41–44], none to our knowledge have considered the effect 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 worker GDP. A previous study attempted to quantify the relationship between social economic agglomeration (similar to occupational distributions from the OES data set [24]) and economic activity; they found a limited relationship between the growth rate of population density and growth rate of labor productivity, supporting our hypothesis that it is not necessarily population density that increases productivity, rather our findings support our claim that it is an increased density of face-to-face interactions that raises labor productivity [45].

While several studies examine the relationship between industry, their resident cities, and the industry's effect on GDP [46–48], none of these studies considered the effect of the density of social activities per worker. While this result points to a promising pathway for increasing worker productivity, further research on how worker socialness affects economic output is needed to confirm this finding.

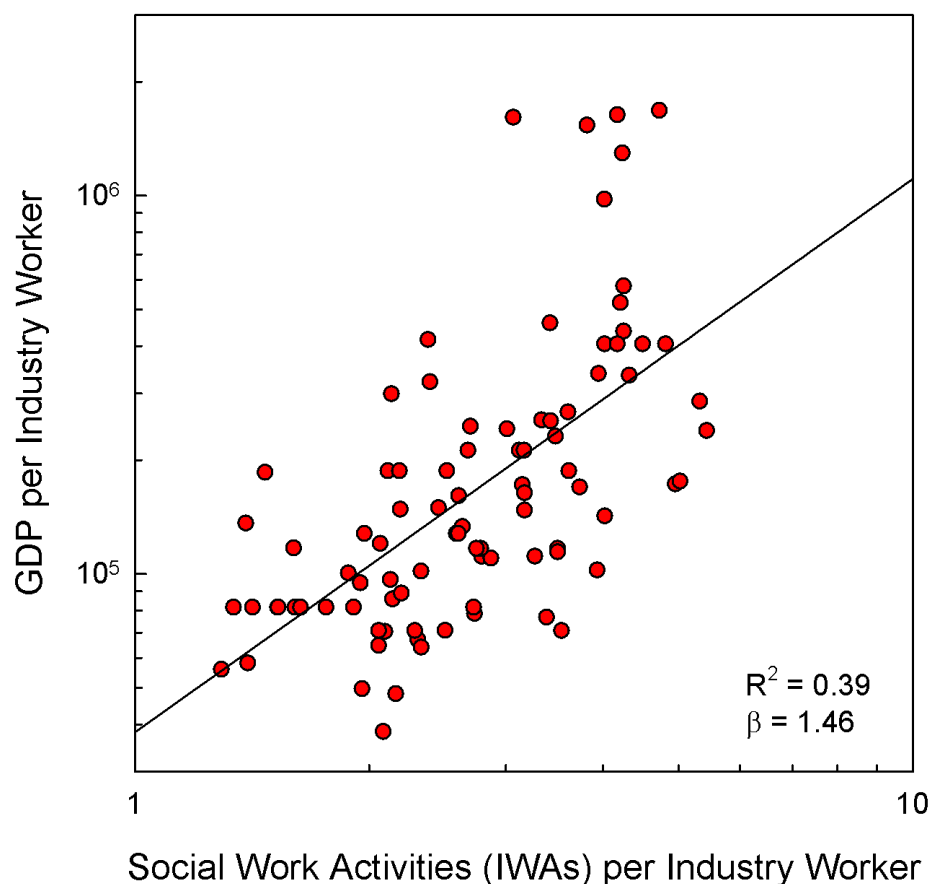


Figure 1. Power-law relationship between GDP and socialness. Both axes are logarithmic. Each dot represents an individual industry for which 2018 GDP and employment data are available ($N = 102$). As the number of social work activities per worker increases, GDP per worker increases superlinearly.

3.3. Implications of the COVID-19 Pandemic

Given the economic importance of worker socialness, it is likely that government policies arising from the COVID-19 pandemic are having significant impacts on economic performance. While social distancing mandates [49], stay-at-home orders [50], and compulsory face mask use [51] are meant to slow the spread of COVID-19, these policies come at a cost of social interactions [52–54]. Social distancing mandates limit the size of gatherings [55] and limit consumer traffic for many businesses [56], depressing the number of face-to-face interactions both between workers and between workers and customers.

The rise in the number of people working remotely [57] or communicating with peers [58] through video conference software such as Zoom leave many workers mentally exhausted and irritable [59]. Our study suggests that this reduction in face-to-face interactions can also result in lower rates of innovation and GDP per worker. While several recent studies note that pandemic-induced restrictions have ill effects on local economies [60–62], these studies do not specifically cite the role of decreased social interactions among workers, but focus instead on policies and their variable implementation. Our study suggests that the reduction in face-to-face interactions is also having a negative economic impact.

3.4. Defining Socialness in the Time of COVID-19

In this study, we have used the concepts of “face-to-face”, “in person”, and “social” almost interchangeably. Yet, to better understand the effects of lockdowns and other COVID-19 restrictions, we should attempt to separate these aspects and their effects. We

conduct work via the internet that one might consider “social activity” but it is not in person. Although we may see each other on a screen, are such interactions truly face-to-face?

Thus, it is important to consider how such distinctions would affect the outcome of our study. While we cannot answer these questions using data from before the pandemic, we believe that replicating our study using data from the COVID-19 period (when it becomes available) will lead to a better understanding of how socialness affects economic activity. More precisely, we may apply our methodology to future data to determine whether the benefits of worker socialness arise through in person interactions, face-to-face interactions regardless of location, or, more broadly, simply through interactions. Understanding such distinctions will have important implications on, for instance, firms offering more work-from home options and those moving to a decentralized workforce. It will also help anticipate the impacts of urban policies designed to attract remote workers and headquarters of decentralized firms.

3.5. Curious Analogies between Cities and Stars

In previous research, it has proved useful to create biological metaphors of cities as “living systems” [63] often having a “metabolism” [64]. While biological metaphors have proven useful historically [65], 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 [66]; later, it was the body as a machine [67] or the brain as a computer [68].

However, in interpreting our results, we are struck by a novel analogy of cities as a physical system rather than a biological system, creating a theoretical implication for framing future research. 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 [20,21], the rate at which hydrogen atoms interact in stellar gas clouds plays a critical role in whether the cloud will ignite into a radiant star 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 [69,70]. 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 worker 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 [71,72]. 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 [73]. 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 [74]. 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 superlinear scaling relationship between worker socialness and industry GDP per worker (economic efficiency) as well as a strong positive correlation between the density of social workers and a city's per worker patent production (innovation).

Moreover, we address concerning implications for a society as public health precautions due to COVID-19 severely reduce social interactions and force many workers to interact only via telephone or video conferencing software. It remains unclear how economic performance will change with global decreases in worker-to-worker interactions, loss of face-to-face communication, and decentralization of firms, especially in the service sector.

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, high-density cities encounter unique risks when attempting to create healthy spaces during this pandemic [75]. We believe a stellar model may offer a novel framework to address these and related questions about recovery after the pandemic.

Supplementary Materials: The following are available at <https://www.mdpi.com/2413-8851/5/1/21/s1>.

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