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Re-designing knowledge production in the Post-Covid-19 era.
A task-based approach

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Abstract. This paper seeks to single out what micro-level working activities may be more conducive of faster Covid-19 transmission. We do so from an innovation perspective, knowing that knowledge production has an important component rooted in tacit knowledge, whose sharing is heavily based on physical interaction. Specifically, we hypothesize that communication-intense working activities (including those needed to transfer tacit knowledge) may accelerate Covid-19 contagion, and must be re-designed with more urgency and attention than other working activities that apparently may look as dangerous, such as selling or training. We test this empirically employing data from 9 different sources relative to US Metropolitan Statistical Areas, and confirm our hypothesis, eventually elaborating policy and managerial implications for dealing with innovation (and beyond) during the pandemic.

Keywords: covid-19, pandemic, organizational processes, micro tasks, professions

JEL classifications: O32

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1. Introduction

Innovation develops through processes of knowledge exchange among individuals within the same organization or across organizations. In some cases, these processes are meant to share knowledge that is not easily transferrable through shared codes (such as patents). This is the case of tacit knowledge, such as know-how (Kogut & Zander, 1992). In these cases firms need to mobilize the locus where tacit knowledge is embedded, i.e., people, and implement processes of collaboration that allow such knowledge's features to be 'executed' and 'shown' by the owner, and thus learned and acquired by the receiver (Nonaka, 1994; Nonaka et al., 2006). Collaboration of this kind develops through meetings, discussions, joint work, and usually imply a tight in-person communication (Bouncken & Aslam, 2019).

In other words, while learning from other firms' patents may be done without any in physical interaction, and other working activities may imply contacts for which in person meetings and interaction may be less crucial (such as selling, negotiating) or can be easily codified and shaped for reducing interpersonal interaction (e.g., teaching, coaching, monitoring, coordinating), communication aimed at transferring tacit knowledge may be impossible to perform without sharing the same physical space; and when in that space, impossible without close unstructured interaction

This type of interaction may however be problematic in the age of Covid-19, i.e., in a world were physical interactions are source of risk for people's health. As indicated in Morawska and Cao (2020) infective molecules loaded with viral content may spread and travel from the source up to a distance of 10 meters, "activating aerosol transmission". A similar claim is made also in Paules et al. (2020) and Setti et al. (2020). Thus, as the world exists from the isolation regime enforced during the pandemic peak, working activities need to be restored having in mind that interpersonal contacts can be source of risk for people's health, and must be treated accordingly to avoid a new spread of COVID-19. This is especially true for R&D and innovation-related activities, whose strong reliance on transfer of tacit knowledge may imply a high frequency and importance of physical interaction.

Centralized policies and changing people habits are only part of the solution. In this paper we link data about Covid-19 transmissions in specific areas of the US (227 Metropolitan Statistical Areas) to data about working activities performed in the same areas by all major occupations in the economy, controlling for other determinant of the virus transmission. The idea is to place under scrutiny the type of interactions happening on the shop floor, in the shops, during services provision, to understand what tasks are conducive to Covid-19 transmission, and thus allow managers and entrepreneurs to re-design contagion-prone processes such that transmission can be limited while the organizations' activity can keep going. We read the result of this analysis applying an innovation perspective, having in mind that knowledge production requires much interaction, and that it may heavily rely on tacit knowledge, a type of knowledge for which *physical* interaction is key (Becker-Beck et al., 2005).

Our result lean toward the idea that Communication-laden working activities and other related activities (such as Interpreting the meaning of information for others, Establishing and maintaining interpersonal relationships, or Negotiating with others) are more conduce of the Covid-9 contagion than other activities, such as Assisting and caring for others or Selling or influencing others, that show no statistical significant effect on the speed of Covid-19 transmission.

Our results are thus relevant for researcher and practitioners in need of identifying transmission-prone tasks with the aim of detecting what processes need to be re-designed to remain safe '*and*' productive, rather than safe '*or*' productive. Particularly, they are relevant for innovation managers, who need to care particularly for transformation and sharing also of the tacit component of knowledge. As a final contribution, we provide a methodology that may prove to be useful to face the new phase of the pandemic.

2.Theoretical background

As we write (May 2020), many Governments worldwide are gradually abandoning the policies implemented before reaching the peak of the Covid-19 pandemic (Business Insider, 2020; The New York Times, 2020). Restrictions to mobility are released, and lockdown orders are replaced by permission to move and undertake activities restricted before, such as -for example- running production plants and selling non-essential goods and services.

However, the pandemic is not over: containing Covid-19 transmission implies that organizations' processes must be redesigned to take into account new safety rules. While the lockdown implied that limiting the contagion was done *instead* of undertaking working activities, now firms need to learn how to do it *while* working. In particular, organizations need to tradeoff between covid-19 transmission likelihood on the one hand, and task effective and efficient completion on the other hand. To do that, they need to act on the way each task is designed and performed. Policies cannot be fine-grained enough to act at such micro-level, nor individual responsibility alone can be considered enough to solve the issue. Entrepreneurs and managers, non-profit leaders and public authorities, need to identify what micro-level working activities are at the highest risk of spreading the contagion, and act to change the relative processes and task design.

There is increasing consensus that the Covid-19 transmission takes place mainly via virus laden droplets in the aerosols produced during individuals' close interaction (Asadi, 2020), either directly by inhalation, or indirectly via "*direct physical contact ... handshaking... sharing of meals ... via fomites and shared food*" (p. 1045, Pung et al., 2020). Thus, any situation that causes close interaction may contribute to the spreading of the contagion, and has to be avoided, or modified to allow for personal protective equipment to be used and social distancing to be applied.

The public debate on this issue focuses on how to handle interaction-laden situations. The key point is the need to unfold the micro-dynamics of interactions to understand what behaviors should be incentivized, how processes should be designed, and how institutional elements should be leveraged to shape encounters and gatherings (e.g., The Conversation, 2020; Erin Bromage: Covid-19 musings, 2020). The scientific debate in medicine also moved along the same direction. For example, Park et al. (2020) studied cases in which transmission occurred in call centers, Ghinai et al. (2020) focused on community and family-related transmission, and Lu et al. (2020) investigated how contagion developed in restaurants.

Despite the attention to the topic, the practical approach applied by now (May 2020) to the problem was geared more to the macro or meso level, for example identifying sectors as units of analysis and producing guidelines generically thought for the archetypical firm in each sector, in a "one size fit all" fashion. This methodology risks to miss the point. For example, Morawska and Cao (2020) show that indoor interaction is a key environmental condition to boost virus contagion, but also signal that both communities and policy makers failed to recognize this fact and act accordingly. Only recently some policy makers tried to 'go more micro' than sectors, and stated the importance of looking at interaction processes and supply chains in their whole complexity (La Repubblica, 2020).

Such a micro perspective can be particularly beneficial when applied to activities whose undertaking implies a high level of interaction among individuals. Knowledge production is certainly one of them.

The seminal work by Nonaka (1994) offered already twenty-five years ago a firm point along this line: "*Although ideas are formed in the minds of individuals … 'communities of interaction' contribute to the amplification and development of new knowledge. … these communities … define a further dimension to organizational knowledge creation, which is associated with the extent of social interaction between individuals that share and develop knowledge. This is referred to as the 'ontological' dimension of knowledge creation*" (Nonaka, p. 15). Thus, conceiving R&D

management in the age of Covid-19 means asking questions on how individuals' interaction should be designed, through which processes and along which channels.

Further investigation of this point allows to identify even better the features of innovation-related interactions that may carry the risk of spreading the contagion. Nonaka (1994) and colleagues (e.g., Nonaka & Konno, 1998; Nonaka & Von Krogh, 2009) developed a conceptual model of knowledge production in organizations based on the 'dialog' between tacit and codified knowledge (Kogut & Zander, 1992), whose different features imply very different organizational arrangements (Nelson & Winter, 1982; Conti et al., 2013). The basic model unfolds through four phases: Socialization, Externalization, Combination and Internalization (the SECI model). The phases represent four different 'moments' in which knowledge conversion between tacit and codified occurs (Nonaka & Von Krogh, 2009). Nonaka et al. (2006, p. 1182) clearly define these moments "*Socialization aims at sharing tacit knowledge among individuals. Externalization aims at articulating tacit knowledge into explicit concepts. Combination aims at combining different entities of explicit knowledge. Internalization aims at embodying explicit knowledge into tacit knowledge*." When individuals engage in Socialization, the processes they need to activate implies co-location almost by definition. Tacit knowledge is in fact context specific, "*tied to the senses, tactile experiences, movement skills, intuition, unarticulated mental models, or implicit rules of thumb … rooted in action, procedures, routines, commitment, ideals, values, and emotions"* (p. 636, Nonaka & Von Krogh, 2009). Sharing tacit knowledge implies going through the same experience together, observing, imitating, interacting (Nonaka & Takeuchi, 1995). Interacting face-to-face is thus not only convenient (Becker-Beck et al., 2005) but necessary (Bouncken & Aslam, 2019; Conti et al., 2013), also in high-tech industries such as software (Ryan & O'Connor, 2013). Working in the same physical spaces becomes so determinant that the features of the common space have a major role in determining how interactions occur (Khazanchi et al., 2018) and thus how knowledge is shared and transferred.

Interacting face-to-face to share tacit knowledge is thus a key feature of knowledge production in organization (Leonard & Sensiper, 1998; Hall & Andriani, 2003). This is true in general, within the organization and also between organizations (Terhorst, 2018; Lawson et al., 2009). Particularly, it is true within R&D labs and departments, where cooperation within internal teams as well as with external innovation sources (Laursen & Salter, 2006) may be a key asset to achieve the gains of knowledge recombination (Thijs & Martin, 2017). In undertaking such cooperation, knowledge tacitness may have important effects on the management of researchers and of research lines (Chuang, et al., 2016). For example, even if virtual R&D teams spanning different locations are becoming a key asset for many R&D departments, one of the limits these have hinges upon the high relevance of tacit knowledge. Indeed, Gassmann & von Zedtwitz (2003) show that governance measures, such as centralization, must be put in place for these teams to compensate the lack of physical interaction and thus the difficulties in sharing tacit knowledge.

This fundamental role of tacit knowledge for innovation is also related to the industrial structure of the specific economy under study. In economies where SME's are a very large share of the value added, like Italy for example, knowledge tacitness may be even more relevant for innovation, as SME's heavily rely on external knowledge resources, on the knowledge embedded in their human resources and on the experience-based mode of knowledge development. Given the limited reach these firms have, all the three factors must be found in the local surroundings, and are usually accessed via interactions whose physical component is key (Valentim et al., 2016). Italy has been heavily hit by the Covid-19 pandemic, and studies show (Becchetti et al., 2020) that this may be due also to the presence of many SME's, corroborating our intuition that the physical proximity needed by these firms to transfer tacit knowledge may be one of the vehicle of Covid-19 transmission.

In line with this idea, in the following section we will run regressions that relate Covid-19 transmission to interaction-laden working activities, irrespectively of the sector they happen to be undertaken. We aim at singling out the role of each working activity to understand precisely what is the impact on the virus diffusion of *communication*-intense activities (and other closely-related activities), that may be conducive of tacit knowledge transfer via physical contact. In other words, we will test the following hypothesis:

Hypothesis: Communication-related activities (and other closely-related activities) accelerate the Covid-19 spreading in the area, while other types of activities have a less prominent role.

3. Methods

In order to investigate which interaction-laden tasks should be seriously considered and possibly re-designed -especially in R&D labs and departments- as we enter the re-opening phase of the late pandemic, we conducted a regression analysis relating speed of Covid-19 transmission on the US territory and diffusion of interaction-laden working activities in Metropolitan Statistical Areas (MSA).

MSA's are geographical regions in the US with at least one urbanized area and a population of at least 50.000 individuals. The US Census Bureau indicates a MSA as "…a core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core". There is a total of 392 MSA's which encompass almost the 85% of the US population.

The number of MSA's we are able to actually use in our regressions is 227. This is due to the list of controls that we included, and that contains several missing values. However, the most representative MSA's remain in the sample. To give an idea, the 227 observed MSA's represent the 74% of all the 392 MSA's in terms of 2019 total population.

We gathered data at MSA (and State) level merging 9 datasets we sought for and gathered online: the *O*NET* dataset (from the U.S. Department of Labor/Employment and Training Administration), and the data provided by the *New York Times*, the *U.S. Bureau of Labor Statistics Latest Numbers*, the *U.S. Bureau of Economic Analysis*, the *U.S. Census Bureau*, the *U.S. Environmental Protection Agency*, the *NBC News*, the *U.S. Department of Health and Human Services*, and the *U.S. Bureau of Transportation* (Table 4 reports which source has been used for building each specific variable).

3.1 Dependent variable

MSA-level data on Covid-19-related deaths in the US are taken from the New York Times public repository[1]. The database contains information on the daily number of registered Covid-19-related deaths across US counties; according to it, the first death occurred in the King county (Washington) on February 29th, 2020. For each MSA we counted the number of days that go from the first Covid-19-related death to the day of the 50th death, of the 100th death and of the 150th death, obtaining three dependent variables.

We chose to use the number of deaths as a proxy for Covid-19 diffusion since the number of infected patients may suffer from severe underreporting, as explained by Buonanno et al. (2020) and Pisano et al. (2020), especially in the early stage of pandemic. This may happen essentially for two reasons. First, there is widespread consensus on the high number of asymptomatic patients that never get tested, biasing the number of detected infections. Second, Covid-19 testing programs may differ across regions even within the same country. These measurement issues are likely to be less concerning for official death records, as these capture the direct observable effects of the virus irrespectively of authorities' testing strategy or of the number of asymptomatic patients. Even if

[1] Data are available at: https://github.com/nytimes/covid-19-data/. The version of the database used in this paper is the one of May 22nd 2020

some differences in the reporting guidelines are there for different countries, we are quite confident that the criteria to mark one death as Covid-19-related are quite consistent across MSA's in the US.

We chose to use three time windows to look at the speed of the contagion (from the first to the 50^{th}, 100^{th} and 150^{th} death) because we had to trade-off between length of the time span (the longer, the better, as erratic behaviors should be less relevant if the time window is large enough) and the number of MSA's reaching the number of deaths we set as threshold (50, 100 and 150), whose numerosity must be high enough to allow for meaningful estimation, but is also decreasing in the length of the time interval. In this sense, considering the three alternatives altogether, as we do, allows for more reliable estimations.

3.2 Independent variables

Each occupation requires different levels of skills and abilities in order to be performed, but most importantly it involves diverse working activities. We focus on the level of interaction-laden working activities within all the 22 major occupations in the MSA[2] as reported in the O*NET dataset (last update: May 2020). In the dataset, the working activity are defined as "a set of similar actions that are performed together in many different occupations". O*NET reports 41 working activities and their relevance (weight) for each of the 22 major occupation. As an illustrative example, take working activity 4.A.4.a.5 (Assisting and Caring for Others): the top three occupations result *Healthcare Practitioners and Technical Occupations, Community and Social Service Occupations, Healthcare Support Occupations*, with weights for that working activity that range between 0.67 to 0.76. The occupations in which the weights for Assisting and Caring for Others are the lowest are instead Computer and Mathematical Occupations, Architecture and Engineering Occupations and Arts, Design, Entertainment, Sports, and Media Occupations (for which the weighting scores lay around 0.25).

Within the 41 working activities, we singled out the 17 interaction-laden activities (grouped under the label "Interacting with others" in O*NET, see Table 1, in bold), and focused only on those. In order to see how spread is each of the 17 working activities in the economy of the MSA we proceeded in three steps. First, we considered the weight each of the 17 working activities was associated with in each occupation present in the MSA. Second, and focusing on one working activity at a time, we retrieved the number of many people employed in each occupation, and multiplied that number by the weight of the working activity in the relative occupation. Third, we summed up across all occupations the 22 terms *(occupation employment * working activity weight)*, and normalized the result by the MSA total employment in 2019. By this measure we obtain an

[2] A list of major occupations is available at https://www.bls.gov/oes/current/oes_stru.htm

estimation of how much diffused and important was a certain working activity in the employed population, normalized for the MSA overall employment.

3.4 Controls

In order to make sure we do not capture spurious correlation between our variables, we introduced a series of controls affecting the Covid-19 speed of contagion.

GDP: GDP per capita in 2019, computed as the ratio between MSA current value GDP (U.S. Bureau of Economic Analysis) and MSA total population (U.S. Census Bureau).

Population Density: the ratio between total population in the MSA in 2019 (U.S. Census Bureau) and MSA squared kilometers. The contagion within MSA's that are more densely populated is likely to accelerate, as social distancing behavior may result more difficult.

Air Quality Index: developed by the U.S. Environmental Protection Agency, the index ranges from 0 to 500 and it is calculated on a daily basis taking into account ground-level ozone, particle pollution, carbon monoxide, and sulfur dioxide. For each MSA, we take the 90th percentile value in the yearly AQI distribution. Becchetti et al. (2020) show that low air quality is a strong predictor of both Covid-19 contagion and mortality rates, thus controlling for it is key.

Death Ratio: number of deaths occurred in each MSA in 2019 divided by 2019 MSA total population (U.S. Census Bureau). The death ratio in the last year is the result of several factors that we believe are linked to key societal and economic specificities of each MSA, such as population age structure, overall population health condition (especially critical conditions) and the well-functioning of the health system. As age and co-morbidity have been associated to higher Covid-19 death rates, and the effectiveness of the healthcare system can greatly impact patients' capability to recover, this is crucial to control to take into account.

Federally Qualified Health Centers: these are "community-based health care providers that receive funds from the HRSA Health Center Program to provide primary care services to persons of all ages, regardless of their ability to pay or health insurance status". The variable is computed as the ratio between the number of users in each MSA Federally Qualified Health Center in 2019 (Centers for Medicare & Medicaid Services, U.S. Department of Health and Human Services) divided by 2019 total population (U.S. Census Bureau). We used it as a proxy for the intensity of access to each MSA health system by the least protected citizens.

Home Health: in addition to Federally Qualified Health Centers, we include the number of users of home-care agencies (from the U.S. Department of Health and Human Services) over total population (U.S. Census Bureau), that provide medical treatment or assistive care for patients who do not require hospitalization or facility care, but do need additional support. As highlighted by Pisano et al. (2020), one of the crucial responses to Covid-19 pandemic adopted by some Italian regions (Veneto in particular) is the strong attention toward home diagnosis and care, so we decided to control for that.

Flight Passengers: we retrieved the number total number of passengers of commercial flights that transited in each MSA in 2018 (U.S. Department of Transportation, Bureau of Transportation Statistics). The variable is computed as the ratio between the number of passengers and total population (U.S. Census Bureau). We use this variable as a proxy for boundary-spanning transportation flows.

Transport: total number of employees in transportation-related business establishment (from Statistics of U.S. Businesses, U.S. Census Bureau), divided by total population. As indicated by Adda (2016), a solid and busy transportation infrastructure may enhance viral contagion. The variable is a reasonable proxy for the level of local-reach transport, mainly within the MSA.

Lockdown: the number of days between the first MSA Covid-19-related death and the date in which the corresponding State activated some Stay-at-Home regulation. Information is taken from the NBC News website[3]. We believe that territory-specific strong policies like the lockdown are a crucial factor in limiting the rate at which the virus diffuses, and also the relative frequencies of the working activities in the economy. This is thus a crucial control.

Descriptive statistics and correlations for all variables can be found in Tables 4 and 5a, 5b and 5c.

3.5 Estimation

[3] https://www.nbcnews.com/health/health-news/here-are-stay-home-orders-across-country-n1168736

Our empirical analysis relates speed of Covid-19 spreading in the MSA with presence of certain interaction-laden working activities in the same area, plus controls. Thus, we rely on the semi-parametric model introduced by Cox (1972), a duration model well suited to estimate speed of events, and define a 'failure' (i.e., the event of interest, whose manifestation is the subject of analysis) as the occurrence of the 50^{th} Covid-19-related death. In two alternative specifications, we define a 'failure' as the occurrence of the 100^{th} and then the 150^{th} Covid-19-related death. As of May 22^{th} 2020 there are 88 MSA that experienced at least 50 Covid-19-related deaths.

In the Cox model duration time is represented by a *hazard function*, which quantifies the instantaneous risk of failure at time t, conditional on survival up to t-1. This conception allows to express relations among the variables via the following function:

$$h_j(t)=h_0(t) * exp(b_i x_i + c_1 z_1 + \ldots + c_8 z_8) \qquad (1)$$

where x_i is the regressors for the working activity i among the 17 constructed from the O*NET data, $[z_1,\ldots,z_8]$ is the list of control variables described in Section 1, and $h_0(t)$ is the baseline hazard -i.e. the hazard when all covariates are set to zero- for MSA j. We rely on the partial likelihood approach described by Cox (1972): the parameters can be estimated without a specific functional form for the baseline hazard, $h_0(t)$. The estimation leads to coefficients that represent hazard ratios, i.e., the ratio between the hazard obtained when the focal regressor increases and the baseline hazard. Thus, a coefficient greater than one implies that increases in the regressor increase the probability of having a failure in each t, de facto accelerating its occurrence, and vice versa for coefficients smaller than the unit.

The Cox model relies on the assumption of proportional hazards: for each covariate, the proportional hazard b_i is assumed to be fixed over time. In order to verify the assumption, after each estimation we conducted a score test based on scaled Schoenfeld residuals, as described in Grambsch and Therneau (1994). The tests confirm that the assumption is met, and we can proceed with the estimation without any problem. Finally, to control for heteroskedasticity due to correlation at a higher level than MSA's, we clustered standard errors across US macro-regions: West, South, Northeast and Midwest.

4. Results

Due the different scales of measurement, we estimate our model after a min-max rescaling transformation of all explanatory variables other than Air Quality Index and Lockdown, whose units of measurement are already in line with the min-max normalization range (see variables' summary statistics in Table 4, reported in original values). Min-max rescaling is a linear transformation that makes coefficients range between 1 and 100. As it is a linear transformation, it preserves the relations among variables. Thus, estimations made with original and with normalized values lead to qualitatively identical results[4], even if with the min-max transformation coefficients become more readily readable.

Due to high correlation among working activities we could not pool all of them into one regression, so we included one activity at a time, running 17 different regressions (one example is given in Table 3). Table 2 reports all the 17 coefficients for our interaction-laden working activities. For 7 out of 17 working activities, we found a positive association between the relative load of interaction-laden working activities and the number of days between the first and the 50th Covid-19-related death. In all cases coefficients are greater than 1 and significant, meaning that these 7 interaction-laden working activities do exert a clear effect on Covid-19 diffusion, accelerating the spreading of the contagion. When extending the analysis to the other two dependent variables, days to the 100th death and to the 150th death, only 3 of the 7 coefficients maintain their significance: those for Interpreting the Meaning of Information for Others; Communicating with Supervisors, Peers, or Subordinates; Communicating with Persons Outside Organization. These *communication*-related activities are those that exert the most durable, solid and clear effect on the spreading of the virus. The other interaction-laden working activities have either no statistically significant effects on Covid-19 speed of transmission, or they have it only for one or two spreading thresholds (i.e., one or two of our three dependent variables), thus providing only weak evidence that that activity has an impact on the virus diffusion. Thus, our hypothesis that communication-related activities contribute significantly to accelerate Covid-19 contagion is confirmed.

To make sure of our results, we run a series of robustness checks. First, as Cox regression is designed for scenarios in which time is a continuous variable, we repeated all the estimates with a discrete-time model. Therefore, we fit the models reported in Table 3 using a parametric model, and estimate coefficients via maximum likelihood[5]. Results were confirmed in all estimations, in terms of both significance and direction of the effect.

Then, we included an additional control in the analysis: the share of population over 65. We know that Covid-19 is extremely dangerous for elder people. We already took that into account controlling for Death Ratio, but age is so relevant in the Covid-9 scenario that it seems worth to include a specific control for it. With such control, however, severe multicollinearity emerges. Indeed, the correlation between the share of people who are 65-years old or older and Death Ratio

[4] These estimates without min-max normalization are available from the authors upon request
[5] We used two alternative parametrizations: Weibull and Lognormal

is very high: 0.78. We thus excluded Death Ratio from the regressions, even if in this case we lose a much wider control for a series of phenomena, such as population age structure, overall population health condition and the well-functioning of the health system (and this is why we prefer to keep in the regression Death Ratio rather than the share of population over 65). These alternative models confirm all the results reported in Table 2 for the case in which the days counted in the dependent variables span the interval from the first Covid-19-related death to the 50th death. However, when moving the threshold to the 100th or the 150th death all coefficients cease to be significant. Thus, we can by and large confirm our results, even if we have to notice that the age structure of the population exerts a quite strong effect on the speed of contagion and related deaths, an effect that grows as the pandemic diffuses, overcoming many of the other factors relevant at the beginning, including diffusion of specific interaction-laden working activities.

5. Discussion and Conclusion

In this paper we tackled the problem of identifying what kind of interaction-laden working activities are more transmission-prone of the Covid-19 virus. The idea is that if some links between the activity and the transmission is found, then we can locate with precision which working activity "activated the transmission", and can be thus considered more risky than others. Firms re-opening their activities in this new phase of the pandemic can use this insight to focus their resources and energies on the redesign of those activities, re-building their value chains and re-shaping their processes to achieve at the same time higher levels of safety *and* productivity.

The angle we used to look at this problem is that of Innovation Studies. We chose this angle because knowledge production is at the same time a key activity of any economic undertaking, and based on heavy interaction among innovators. This is clear when we look at knowledge-production activities aimed at sharing a specific and crucial component of knowledge: tacit knowledge. As this type of knowledge in embodied in people (e.g., know-how) and codifying it may be very costly (Nelson and Winter, 1982) physical interaction is a crucial vehicle for sharing it (Nonaka, 1994). As the Covid-19 virus exploits physical proximity to diffuse, we put forward the hypothesis that communication-intense activities such as those needed to share tacit knowledge may be conducive of the contagion, and thus need to be re-designed by R&D managers and project leaders.

We tested this idea gathering data from 9 different sources that relate the speed of Covid-19 transmission in MSA’s in the US to the presence of interaction-laden tasks in the same areas, and found confirmation for our hypothesis: communication-intense activities do accelerate the diffusion of the virus, while other activities show either weak or no statistically significant effect.

This result contributes to the literature and to managers’ insights in three ways.

First, we identify what kind of working activities accelerate Covid-19 contagion. This is done across all major occupations in the US economy, and thus has broad implications for strategy and policy: to achieve safety *and* re-ignition of economic activity at the same time, managers and authorities need to consider that re-shaping communication-related activities is more relevant than acting on other operations. In detail, we found that activities that are quite central to our social and economic system, such as Assisting others, Training, Directing Subordinates, Selling and the like, have *not* the same striking effects of communication-intense activities. This means that, when imagining how to adapt our economic system to this new phase of the Covid-19 pandemic, the latter should receive more attention than the former for the contagion-risk they imply. Processes that heavily rely on these activities must be re-thought and re-designed, as they are the most conducive of the transmission. This has broad implications for managers, as acting on communication tasks implies redesigning fundamental features of the organization, if not the whole interaction mode of the organization altogether.

Second, our results speak directly to one of the most important activity in the economy: knowledge production. The link between communication-intense activities and virus diffusion has heavy implications for any firm, as innovation processes heavily rely on tacit knowledge (Nelson & Winter, 1982; Kogut & Zander, 1992), which is mainly conveyed via physical interaction (Nonaka, 1994). R&D managers and innovation project leaders -and researchers in the Innovation Studies academic community- need to think how to re-design knowledge production processes keeping in mind that sharing tacit knowledge cannot be performed in the same way as before. Virtual teams may be conceived as the new arena where digital communication may be conducive of such sharing, but in this case new ways of interaction must be thought, as the digital space may show important limits in this sense (Gassmann & von Zedtwitz, 2003). Alternatively, interaction activities may imply a physical component, but then strict safety measures must be imagined and applied.

Third, our statistical exercise is useful to test a methodology based on micro-processes that, to the best of our knowledge, has received much less attention than it deserves. Of course, our data are not as detailed as they should be. We would need to look at specific ‘situations’ of contagion, and retrieve from those the tasks that are prone to virus diffusion. But even at our larger scale, and gathering data only among freely available sources, we are able distinguish between risk of doing things in certain ways rather than others, providing organizations with knowledge they can use to diminish risk of transmission while remaining active. We thus proved the relevance of a micro perspective that can lead to important results as our societies adapt to the pandemic. Better, i.e., more micro, data are needed for this methodology to produce even more precise results than ours, but we believe that this paper opens a perspective that is certainly worth to be explored. We just opened the door, hoping that researchers with better skills and data than us would decide to walk through it for the good of us all.

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TABLES

Table 1. Interaction-laden working activities (independent variables)

Table 1.

working activities ID	working activities Name
4.A.1.a.1	Getting Information
4.A.1.a.2	Monitor Processes, Materials, or Surroundings
4.A.1.b.1	Identifying Objects, Actions, and Events
4.A.1.b.2	Inspecting Equipment, Structures, or Material
4.A.1.b.3	Estimating the Quantifiable Characteristics of Products, Events, or Information
4.A.2.a.1	Judging the Qualities of Things, Services, or People
4.A.2.a.2	Processing Information
4.A.2.a.3	Evaluating Information to Determine Compliance with Standards
4.A.2.a.4	Analyzing Data or Information
4.A.2.b.1	Making Decisions and Solving Problems
4.A.2.b.2	Thinking Creatively
4.A.2.b.3	Updating and Using Relevant Knowledge
4.A.2.b.4	Developing Objectives and Strategies
4.A.2.b.5	Scheduling Work and Activities
4.A.2.b.6	Organizing, Planning, and Prioritizing Work
4.A.3.a.1	Performing General Physical Activities
4.A.3.a.2	Handling and Moving Objects
4.A.3.a.3	Controlling Machines and Processes
4.A.3.a.4	Operating Vehicles, Mechanized Devices, or Equipment
4.A.3.b.1	Interacting With Computers
4.A.3.b.2	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
4.A.3.b.4	Repairing and Maintaining Mechanical Equipment
4.A.3.b.5	Repairing and Maintaining Electronic Equipment
4.A.3.b.6	Documenting/Recording Information
4.A.4.a.1	**Interpreting the Meaning of Information for Others**
4.A.4.a.2	**Communicating with Supervisors, Peers, or Subordinates**
4.A.4.a.3	**Communicating with Persons Outside Organization**
4.A.4.a.4	**Establishing and Maintaining Interpersonal Relationships**
4.A.4.a.5	**Assisting and Caring for Others**
4.A.4.a.6	**Selling or Influencing Others**
4.A.4.a.7	**Resolving Conflicts and Negotiating with Others**
4.A.4.a.8	**Performing for or Working Directly with the Public**
4.A.4.b.1	**Coordinating the Work and Activities of Others**
4.A.4.b.2	**Developing and Building Teams**
4.A.4.b.3	**Training and Teaching Others**
4.A.4.b.4	**Guiding, Directing, and Motivating Subordinates**
4.A.4.b.5	**Coaching and Developing Others**
4.A.4.b.6	**Provide Consultation and Advice to Others**
4.A.4.c.1	**Performing Administrative Activities**
4.A.4.c.2	**Staffing Organizational Units**
4.A.4.c.3	**Monitoring and Controlling Resources**

Table 2. Coefficients of the interaction-laden working activities in our 17 regressions

Focal regressor	50 deaths	100 deaths	150 deaths
Interpreting the Meaning of Information for Others	**1.014*** **	**1.018***	**1.025*** **
	(0.0042)	**(0.0110)**	**(0.0085)**
Communicating with Supervisors, Peers, or Subordinates	**1.018*** **	**1.021*** **	**1.026*** **
	(0.0067)	**(0.0013)**	**(0.0092)**
Communicating with Persons Outside Organization	**1.017*** **	**1.021** **	**1.023***
	(0.0058)	**(0.0089)**	**(0.0140)**
Establishing and Maintaining Interpersonal Relationships	**1.013** **	**1.016***	1.020
	(0.0053)	**(0.0090)**	(0.0129)
Assisting and Caring for Others	0.993	0.999	1.002
	(0.0123)	(0.0071)	(0.0104)
Selling or Influencing Others	1.004	1.005	0.999
	(0.0057)	(0.0055)	(0.0173)
Resolving Conflicts and Negotiating with Others	**1.015** **	**1.020***	1.019
	(0.0064)	**(0.0113)**	(0.0201)
Performing for or Working Directly with the Public	0.999	1.007	1.006
	(0.0112)	(0.0089)	(0.0158)
Coordinating the Work and Activities of Others	1.012	1.017	1.0126
	(0.0105)	(0.0174)	(0.0178)
Developing and Building Teams	1.010	1.015	1.012
	(0.0089)	(0.0151)	(0.0145)
Training and Teaching Others	1.001	1.009	1.015
	(0.0050)	(0.0139)	(0.0119)
Guiding, Directing, and Motivating Subordinates	1.004	1.009	1.002
	(0.0087)	(0.0146)	(0.0159)
Coaching and Developing Others	1.004	1.010	1.011
	(0.0058)	(0.0124)	(0.0141)
Provide Consultation and Advice to Others	**1.013** **	1.015	1.014
	(0.0059)	(0.0112)	(0.0106)
Performing Administrative Activities	**1.010** **	1.011	1.015
	(0.0050)	(0.0078)	(0.0101)
Staffing Organizational Units	1.003	1.006	0.998
	(0.0067)	(0.0095)	(0.0127)
Monitoring and Controlling Resources	1.003	1.002	0.990
	(0.0095)	(0.0116)	(0.0160)
Observations	227	227	227
Failures	71	44	32
Controls	Y	Y	Y

Exponentiated coefficients; Standard errors, clustered at the region level, are reported in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3. Example of one of the 17 regressions

	(1)	(2)	(3)
	50 days	100 days	150 days
Interpreting the Meaning	**1.014***	**1.018***	**1.026***
of Information for Others	**(0.00422)**	**(0.0110)**	**(0.00855)**
GDP	1.001	1.005	1.008
	(0.0108)	(0.0156)	(0.0164)
Population Density	**1.131***	**1.135***	**1.127***
	(0.0280)	**(0.0340)**	**(0.0277)**
Air Quality Index	**1.038***	**1.041***	**1.050***
	(0.00903)	**(0.00946)**	**(0.00998)**
Lockdown	**0.983***	**0.968***	**0.940***
	(0.0105)	**(0.0147)**	**(0.0125)**
Home Health	0.958**	0.963	0.872
	(0.0183)	(0.0309)	(0.207)
Death Ratio	1.002	**1.018***	**1.038***
	(0.00362)	**(0.00643)**	**(0.0186)**
Federally Qualified Health Centers	0.990	0.974	0.953
	(0.00748)	(0.0330)	(0.0304)
Flight Passengers	**1.019***	1.019	**1.048***
	(0.00916)	(0.0188)	**(0.0159)**
Transport	**1.029***	**1.055***	**1.055***
	(0.0130)	**(0.0115)**	**(0.0146)**
Observations	227	227	227
Failures	71	44	32
Chi-squared	126.4	213.6	65.26

Exponentiated coefficients; Standard errors, clustered at the region level, are reported in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 4. Descriptive statistics and data sources

	Mean	Std. Dev.	Min	Max	Source
Interpreting the Meaning of Information for Others	.41	.011	.381	.449	O*NET; USBLS
Communicating with Supervisors, Peers, or Subordinates	.584	.008	.564	.609	O*NET; USBLS
Communicating with Persons Outside Organization	.474	.014	.43	.511	O*NET; USBLS
Establishing and Maintaining Interpersonal Relationships	.631	.008	.606	.653	O*NET; USBLS
Assisting and Caring for Others	.428	.012	.399	.495	O*NET; USBLS
Selling or Influencing Others	.349	.009	.323	.375	O*NET; USBLS
Resolving Conflicts and Negotiating with Others	.476	.009	.447	.499	O*NET; USBLS
Performing for or Working Directly with the Public	.459	.013	.409	.492	O*NET; USBLS
Coordinating the Work and Activities of Others	.455	.006	.439	.474	O*NET; USBLS
Developing and Building Teams	.387	.006	.372	.406	O*NET; USBLS
Training and Teaching Others	.46	.008	.437	.493	O*NET; USBLS
Guiding, Directing, and Motivating Subordinates	.388	.007	.368	.409	O*NET; USBLS
Coaching and Developing Others	.454	.008	.434	.483	O*NET; USBLS
Provide Consultation and Advice to Others	.412	.012	.39	.454	O*NET; USBLS
Performing Administrative Activities	.372	.009	.346	.399	O*NET; USBLS
Staffing Organizational Units	.256	.008	.236	.281	O*NET; USBLS
Monitoring and Controlling Resources	.366	.006	.348	.384	O*NET; USBLS
Days to 50th death	39.546	12.811	9	73	New York Times
Days to 100th death	43.357	11.915	9	73	New York Times
Days to 150th death	44.841	11.297	9	73	New York Times
GDP	29.39	12.472	1.118	77.456	US Bureau of Economic Analysis
Population Density	176.724	155.452	11.643	980.845	US Census Bureau
Air Quality Index	59.555	12.791	1	105	US Environmental Protection Agency
Lockdown	16.269	13.71	-9	91	NBC News
Home Health	.011	.012	.002	.175	US DHHS
Death Ratio	.009	.002	.004	.018	US Census Bureau
Federally Qualified Health Centers	.005	.007	0	.052	US DHHS
Flight Passengers	1.287	2.789	0	32.894	US Bureau of Transportation
Transport	.001	.001	0	.014	US Census Bureau

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Interpreting the Meaning of Information for Others	1.000																
(2) Communicating with Supervisors, Peers, or Subordinates	0.967	1.000															
(3) Communicating with Persons Outside Organization	0.795	0.833	1.000														
(4) Establishing and Maintaining Interpersonal Relationships	0.835	0.848	0.971	1.000													
(5) Assisting and Caring for Others	0.144	0.039	0.161	0.333	1.000												
(6)days_1to50_deaths	-0.139	-0.172	-0.104	-0.103	0.042	1.000											
(7)days_1to100_deaths	-0.090	-0.091	-0.016	-0.038	-0.045	0.849	1.000										
(8)days_1to150_deaths	-0.086	-0.068	0.016	-0.015	-0.077	0.730	0.954	1.000									
(9)gdppc2	0.051	0.044	-0.029	-0.064	-0.123	-0.034	-0.053	-0.057	1.000								
(10)pop_dens	0.145	0.222	0.208	0.169	-0.199	-0.345	-0.143	0.001	-0.025	1.000							
(11)aqi90	0.027	0.096	0.067	0.052	-0.099	-0.260	-0.145	-0.066	-0.041	0.319	1.000						
(12)statelock_firstcont	0.094	0.165	0.200	0.153	-0.156	0.065	0.147	0.173	-0.047	0.178	0.069	1.000					
(13)home_health_users	-0.149	-0.127	-0.073	-0.078	-0.015	-0.041	-0.079	-0.091	-0.107	-0.039	-0.024	-0.077	1.000				
(14)death_ratio	-0.440	-0.444	-0.317	-0.293	0.236	0.004	-0.062	-0.057	-0.090	-0.045	-0.100	-0.256	0.153	1.000			
(15)fqhc_users	-0.111	-0.112	-0.077	-0.062	0.060	-0.000	-0.081	-0.119	-0.031	-0.218	-0.022	-0.208	0.546	0.227	1.000		
(16)pass18	0.032	0.125	0.180	0.121	-0.229	-0.167	-0.091	-0.041	0.012	0.285	0.232	0.231	0.639	-0.236	0.276	1.000	
(17)transp_empl	0.078	0.089	0.012	0.035	0.015	-0.198	-0.233	-0.216	0.203	0.057	0.052	-0.011	0.459	-0.071	0.211	0.553	1.000

Table 5. Correlations (b)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)Selling or Influencing Others	1.000																	
(2)Resolving Conflicts and Negotiating with Others	0.893	1.000																
(3)Performing for or Working Directly with the Public	0.615	0.704	1.000															
(4)Coordinating the Work and Activities of Others	0.677	0.782	0.281	1.000														
(5)Developing and Building Teams	0.695	0.843	0.349	0.973	1.000													
(6)Training and Teaching Others	0.324	0.545	0.295	0.753	0.793	1.000												
(7)days_1to50_deaths	-0.022	-0.092	0.034	-0.084	-0.103	-0.032	1.000											
(8)days_1to100_deaths	0.063	-0.013	0.024	-0.011	-0.034	-0.057	0.849	1.000										
(9)days_1to150_deaths	0.100	0.023	0.027	0.001	-0.020	-0.092	0.730	0.954	1.000									
(10)gdppc2	-0.085	-0.073	-0.146	0.091	0.053	0.063	-0.034	-0.053	-0.057	1.000								
(11)pop_dens	0.217	0.208	-0.046	0.161	0.185	-0.038	-0.345	-0.143	0.001	-0.025	1.000							
(12)aqi90	0.045	0.081	-0.047	0.013	0.035	-0.116	-0.260	-0.145	-0.066	-0.041	0.319	1.000						
(13)statelock_firstcont	0.240	0.188	0.029	0.196	0.178	0.020	0.065	0.147	0.173	-0.047	0.178	0.069	1.000					
(14)home_health_users	0.012	-0.036	0.023	-0.103	-0.108	-0.118	-0.041	-0.079	-0.091	-0.107	-0.039	-0.024	-0.077	1.000				
(15)death_ratio	-0.159	-0.207	0.117	-0.397	-0.381	-0.381	0.004	-0.062	-0.057	-0.090	-0.045	-0.100	-0.256	0.153	1.000			
(16)fqhc_users	-0.063	-0.034	0.039	-0.125	-0.116	-0.068	-0.000	-0.081	-0.119	-0.031	-0.218	-0.022	-0.208	0.546	0.227	1.000		
(17)pass18	0.248	0.193	0.001	0.156	0.142	-0.069	-0.167	-0.091	-0.041	0.012	0.285	0.232	0.231	0.639	-0.236	0.276	1.000	
(18)transp_empl	-0.062	0.012	-0.059	0.034	0.059	0.045	-0.198	-0.233	-0.216	0.203	0.057	0.052	-0.011	0.459	-0.071	0.211	0.553	1.000

Table 5. Correlations (c)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)Guiding, Directing, and Motivating Subordinates	1.000																	
(2)Coaching and Developing Others	0.905	1.000																
(3)Provide Consultation and Advice to Others	0.905	0.929	1.000															
(4)Performing Administrative Activities	0.806	0.894	0.920	1.000														
(5)Staffing Organizational Units	0.945	0.898	0.934	0.913	1.000													
(6)Monitoring and Controlling Resources	0.956	0.830	0.899	0.814	0.965	1.000												
(7)days_1to50_deaths	-0.052	-0.066	-0.110	-0.118	-0.060	-0.024	1.000											
(8)days_1to100_deaths	0.007	-0.041	-0.030	-0.040	0.017	0.061	0.849	1.000										
(9)days_1to150_deaths	0.013	-0.048	-0.010	-0.012	0.040	0.080	0.730	0.954	1.000									
(10)gdppc2	0.064	0.028	0.045	-0.064	0.007	0.036	-0.034	-0.053	-0.057	1.000								
(11)pop_dens	0.139	0.091	0.219	0.216	0.208	0.200	-0.345	-0.143	0.001	-0.025	1.000							
(12)aqi90	-0.007	-0.032	0.045	0.080	0.044	0.014	-0.260	-0.145	-0.066	-0.041	0.319	1.000						
(13)statelock_firstcont	0.198	0.113	0.181	0.166	0.219	0.224	0.065	0.147	0.173	-0.047	0.178	0.069	1.000					
(14)home_health_users	-0.081	-0.106	-0.116	-0.084	-0.074	-0.071	-0.041	-0.079	-0.091	-0.107	-0.039	-0.024	-0.077	1.000				
(15)death_ratio	-0.354	-0.382	-0.418	-0.310	-0.315	-0.298	0.004	-0.062	-0.057	-0.090	-0.045	-0.100	-0.256	0.153	1.000			
(16)fqhc_users	-0.110	-0.087	-0.119	-0.075	-0.114	-0.101	-0.000	-0.081	-0.119	-0.031	-0.218	-0.022	-0.208	0.546	0.227	1.000		
(17)pass18	0.156	0.058	0.148	0.137	0.192	0.196	-0.167	-0.091	-0.041	0.012	0.285	0.232	0.231	0.639	-0.236	0.276	1.000	
(18)transp_empl	0.024	0.048	0.065	0.039	0.034	0.020	-0.198	-0.233	-0.216	0.203	0.057	0.052	-0.011	0.459	-0.071	0.211	0.553	1.000