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The Fragility of Urban Social Networks
- Mobility as a City Glue -

CRED Research Paper No. 38

Pierre Magontier
University of Bern, CRED and Universitat de Barcelona, IEB

Maximilian v. Ehrlich
University of Bern, CRED

Markus Schläpfer
University of Bern, CRED and Nanyang Technological University, NTU

July, 2022

Abstract

Social interactions are crucial to a city's cohesion, and the high frequency of interaction reflects many benefits of density. However, adverse environmental conditions, such as pollution or pandemics, may critically affect these interactions as they shift preferences over meeting locations and partners. Some interactions may be shifted to the virtual space, while other non-planned interactions may disappear. We analyze spatial interaction networks in Singapore covering about half of the adult population at a fine-grained spatial resolution to understand the importance of population mixing and places' amenities for urban network resilience. We document that environmental shocks negatively affect total interactions. Still, conditional on meeting physically, the number and type of location options may crucially impact the intensity and type of social interactions. The interplay between preferences for meetings partners, locations, and mobility determines population mixing and the fragility of urban social networks.

Key words: Urban interactions, networks, mobility, environmental shocks

JEL classification: R1, R2, L14

CRED
Universität Bern
Schanzeneckstrasse 1
Postfach
CH-3001 Bern

Tel. +41 31 684 37 11
info@cred.unibe.ch
www.cred.unibe.ch

> *"Man is by nature a social animal; an individual who is unsocial naturally and not accidentally is either beneath our notice or more than human. Society is something that precedes the individual."*
>
> — Aristotle, *Politics*, 4th century B.C.

1 Introduction

Social interactions are the bedrock of any community. Cities bring about crucial density benefits by fostering diverse social interactions. At the individual level, social interactions are the product of preferences over both meeting partners and meeting locations. However, while the economic literature has extensively focused on the outcomes of social interactions and the related endogeneity issues[1] – e.g., to study peer-effects, knowledge spillovers, criminal networks, or consumption behaviors (Glaeser, 1999; Batty, 2013; Helsley and Zenou, 2014; Blume et al., 2015; Jackson et al., 2017; De Giorgi et al., 2020; Atkin et al., 2022), little is known about how shocks on preferences for meeting partners and places affect urban social interactions. What are the social ties and places that glue a city's network together?

This paper presents novel facts about how preferences shape urban social networks for meeting places and partners. We analyze a time series of meetings to study how meetings adjust to adverse conditions. In many aspects, the urban form fosters social interactions. Some public infrastructures such as parks and community centers are, in essence, designed to support meetings and population mixing. However, environmental shocks, such as urban heat, air pollution, or the COVID-19 pandemic affect or constrain preferences for meeting partners and meeting locations. In turn, these mobility frictions limit the number and type of social interactions. Given that environmental shocks are expected to become more frequent and intense (IPCC, 2019), understanding the role of locations in mitigating these adverse impacts on the urban social network is of prime importance.

Yet, despite its relevance, the impact of adverse environmental shocks on social interactions in cities has hardly been explored systematically. Here, we address this gap by analyzing society-wide spatial interaction networks in Singapore at a fine-grained spatial resolution. Our

[1] The literature workhorse, Manski (1993), underlines the *reflection problem* for linear-in-means network models – i.e., the difficulty for the researcher to disentangle peer effects from contextual effects. See Boucher and Fortin (2016) for a discussion of the issues and solutions highlighted by the recent literature.

analysis builds on a unique dataset on mobility and meetings covering more than half of the adult population of this country. We focus on leisure time meetings to ensure that individuals' preferences for meeting places and partners determine the meeting network rather than job-related patterns. The consumption value of cities has been studied in Glaeser et al. (2001); Davis et al. (2019) and recently highlighted in Miyauchi et al. (2022). While we acknowledge adverse meeting conditions are likely to impact work-related interactions, we believe that labor days do not inform us about how networks adapt to shocks because the working environment determines most meeting partners and places. Singapore generally provides a particularly well-suited case to analyze city networks as it displays a high population density and a diverse population composition of different ethnic backgrounds. Urban planning in Singapore intensely and openly aims at fostering spatial interactions through various measures (e.g., parks, events, residential quotas, etc.). Thus, it may provide an 'upper bound' of spatial interactivity, and we may expect more drastic disconnection effects in more decentrally organized cities.

We first show that specific meeting ties of the city network are bridging clusters (i.e., otherwise independent groups of individuals) within the city. We characterize these bridging ties in terms of their network and sociodemographic characteristics. These ties are important for the city network not to collapse into many independent clusters – or 'villages'. These bridges between network clusters are particularly fragile during adverse meeting conditions. Unlike close tie meetings, those fragile ties that link different network clusters are mostly non-planned meetings and can thus not be substituted by virtual interactions. While this paper investigates how mobility patterns affect the network adaptation to shocks, we compute the substitution rate between face-to-face and digital meetings for different categories of individuals and ties in a related project.

Our main results are striking but intuitive. First, meeting probability declines on average by 81 percent during the strict COVID measures and by 5 to 8 percent during adverse environmental conditions. Second, we find that the COVID-19 and environmental shocks significantly affect the relative desirability of locations. For instance, high pollution makes meetings in parks less attractive, whereas high temperatures make them more appealing. We then document that while shocks negatively affect total interactions at the extensive margin, fewer meeting location possibilities may foster population mixing for those who still decide to meet. In other words, there is a trade-off between total interactions and mixing opportunities determined mainly by meeting location diversity. Accordingly, adverse shocks indirectly affect exposure to people's diversity, bridge creation, and survival. Overall, the COVID-19 shock led to a less diverse meeting environment (measured by the network overlap of individuals), while the environmental shocks led to a more diverse network. These effects crucially depend on how shocks affect certain places with different amenities. Places' diversity is shown to help mitigate mobility shocks on the city's network.

While most of the existing work abstracts away this spatial dimension, some more recent papers link social interactions and urban structure (Mossay and Picard, 2011; Zenou, 2013; Sato and Zenou, 2015; Moro, Calacci, Dong, and Pentland, 2021). Closer to our work is Patacchini, Picard, and Zenou (2015), which specifically study how agents' locations affect social interactions between them. In their framework, agents meet with everyone else, deciding the frequency of meetings with every other agent to maximize their utility. The distance between two agents symmetrically defines costs. Nevertheless, although this paper recognizes the importance of agents' location for interactions, it does not incorporate the possibility of different agents having different preferences over locations. We rather assume that agents meet not only because they are close to one another but also because there is a suitable place to meet (according to their preferences) close enough to both.

Other recent studies have empirically documented the importance of population density for forming social networks (Schläpfer et al., 2014; Bailey et al., 2020; Büchel and Ehrlich, 2020; Kim et al., 2020). We add to this literature by exploring the role of specific places and the consequences of adverse conditions for regular meetings of individuals. Another related strand of literature focuses on social homophily and mobility. Recent contributions include Athey et al. (2020); Davis et al. (2019); Abbiasov (2021). These papers often proxy social segregation with spatial segregation. The consequences of COVID-19 on mobility are studied in Couture et al. (2021). Larcom et al. (2017) analyzed the persistent mobility responses to a shock in London's tube system caused by a strike. These papers focus on individual mobility without providing direct insights about the (probability of) meetings of individuals from different population groups and thus mixing within cities. We also contribute to the literature on environmental shocks. While the impact of adverse environmental conditions has been studied for amenities (e.g., Rappaport (2007)), disamenities (e.g., Heilmann et al.

(2021)), urban development (e.g., Kocornik-Mina et al. (2020)), and housing prices (e.g. Barrage and Furst (2019)), to the best of our knowledge, our analysis is the first to study the consequences for urban interactions.[2]

2 Inferring spatial interaction networks

Our analysis focuses on a network realized via face-to-face meetings. We generally understand those meetings as the co-locations of two individuals in a granular space and for a minimum time window.

2.1 Weighted interaction networks

The empirical analysis builds on anonymized trajectory data (time-stamped location records) derived from mobile phone records of the main provider. The data cover approximately 4.1 million mobile subscribers of Singapore's largest telecommunication service provider. Notably, the network is directly obtained from the cell phone provider such that mobility is observed independent of the use of specific apps. The networks are based on pre-existing stay-location data, including socio-demographic attributes (age, gender, and ethnicity). We drop all individuals for which we lack socio-demographic attributes, could opt out of data usage, and require individuals to be active regularly in the observed time period. This brings the number of individuals included in the analysis to about 1.2 million. We model the anonymized mobile phone users as nodes and their socio-demographic attributes as node attributes. We define a link between each pair of nodes if two individuals share the same space during the same time.[3] To that end, we partition the urban space into regular hexagons with a side length of 25 meters and discretize time into regular intervals of 30 minutes. A meeting of two individuals, and thus a link in the network, is then defined as an observation of the two individuals being within the same hexagon within the same time interval. The weight of a link represents the total number of time intervals that two users spent together within the same hexagon. However, despite the high granularity of our spatial resolution, we cannot observe whether two individuals actually interacted with each other. Hence, our measure may also be under-

[2] See also Dell et al. (2014) for an overview.

[3] To ensure the anonymity of the data, we do not observe the time of the meeting.

stood as a co-location that enables a potential interaction. To isolate intentional meetings, we also use repeated co-locations at different locations within the same day or across days. Our analysis focuses on leisure time meetings where individuals flexibly choose whom to meet and where to go while we abstract from work-related meetings. Thus, we focus on the meeting networks observed on Sundays. Table A 1 shows the descriptive statistics for meetings on a "base Sunday". We observe, on average, about 111 million meetings as defined above. The average time spent on these meetings amounts to about 4 hours and 15 minutes with a standard deviation of two hours and 51 minutes. The lion's share of these meetings took place in the home area as defined by Singaporean planning areas (see Figure A.1). Other very popular meeting areas include parks (more than two hours on average) and the downtown area (about one hour of meetings).

2.2 Meeting locations

We observe meetings at different locations, which we classify into location types such as parks, shopping malls, community centers, residential neighborhoods, etc. Figure 1 displays the density of meetings on a base day (no adverse conditions) for the Singapore 'planning areas' (granular census areas). While we observe whether each pair of individuals met within small hexagons, we can only infer the location of these hexagons at a much more aggregated level to preserve the anonymity of the data. Singapore comprises 55 planning areas for which we link detailed information about the type of activities, land use, residential composition, etc. In addition, we estimate the home location of each user by following a common procedure Schläpfer et al. (2021). Specifically, we select as home location the planning area which has been most frequently visited (number of distinct days) by the user. If the user visited several planning areas with the same maximum frequency, we would select the area where the user spent most of his/her time (as far as measured through the spatial interactions). The comparison of our inferred home locations with the census data shows a strong correlation ($R = 0.99$, see Fig. A.2).

We further distinguish between face-to-face meetings that take place in different planning areas such as the downtown core of the city $L^{downt.}$ and the most L^{most} versus least frequently visited planning areas L^{least}. The latter is obtained as the ratio of bilateral meetings per squared kilometer. Another meeting place we distinguish are parks L^{park}, which are inferred from more disaggregated location data.

2.3 Types of shocks

We study three types of adverse meeting conditions influencing the costs of physical meetings. The first type covers different intensities of mobility restrictions during the COVID-19 pandemic. These scenarios imply not only that the costs of meetings increase due to the risk of virus infections, but they also reflect restrictions aimed at a coordinated reduction in physical meetings. The second and third scenarios reflect adverse environmental conditions that changed the costs of meetings at specific places. For instance, urban heat may have increased the average costs of travel but reduced the relative costs of meeting in parks or shopping malls that shelter from the heat.

- *COVID 1*: "circuit breaker"; during this time workplaces were closed and home schooling was mandatory. Moreover, restaurants were closed and no private visits of friends and family were possible..

- *COVID 2*: "safe reopening"; work from home if possible; some services reopen; visit of 2 person (parents, grandparents); limited school attendance.

- *COVID 3*: "safe transition"; retail businesses open; dine-in at restaurants; sports other public facilities open.

- *Pollution*: 24-hour PSI (Pollutant Standards Index) > 90-100; unhealthy level (next: very unhealthy, hazardous). See Figure A.4 for time variation in the degree of air pollution in Singapore.

- *Heat*: $\geq 25\%$ increase of temperature over the monthly mean (7.5 degree celsius)

The most pronounced increase in meeting costs occurs during *COVID 1.* This is the early phase of the pandemic and is an important reference point because it represents the maximum restriction of meetings we have possibly seen so far in modern cities. This was the time of the circuit breaker when workplaces were closed, schooling took place at home, all restaurants and shops except grocery shops were closed, and no private visits of friends were allowed. The other shocks are much less pronounced and different in several ways. Urban heat and pollution are adverse meeting conditions expected to become more frequent with climate change and urban growth. Moreover, these shocks do not lead to coordinated reductions in meetings, but people respond individually via their location preferences. In the following, we denote the shocks, i.e. day conditions by $T^{pollution}$, T^{heat}, T^{COVID1}, T^{COVID2} and T^{COVID3} where the reference condition is the base day with normal meeting conditions (absence of adverse conditions).

3 Aggregate network fragility and importance of ties

How fast does the aggregate network collapse into a separate cluster during adverse meeting conditions? To quantify the aggregate fragility of the spatial interaction networks, we apply the framework of 'percolation analysis'(Newman, 2010). This also allows us to identify essential links for network stability. Specifically, we probe the network's connectivity by counting the number of nodes (size), G, of the 'giant component,' being the largest connected set of nodes. We study this quantity as a function of the progressive removal of network links, with each link removal simulating the loss of a specific spatial interaction between two individuals. The fragility of the network is then given by the number of links that need to be removed so that the network becomes totally fragmented: the sooner the network fragments, the more fragile it is.

As shown in Figure 1, the interaction network becomes more fragile under adverse conditions, further depending on the nature of the condition.

Most of the adverse conditions considered in this study lead to an effective reduction in the spatial interactions and thus to a reduction in the network's connectivity as reflected in a lower average degree $\langle k \rangle$ (average number of links per individual). This connectivity loss explains the increased fragility of the networks under adverse conditions (a lower number of links needs to be removed to induce a complete network disconnection).

An important question arises as to whether adverse conditions may not only decrease the number of links but also lead to systematic changes in the network *structure* that may further

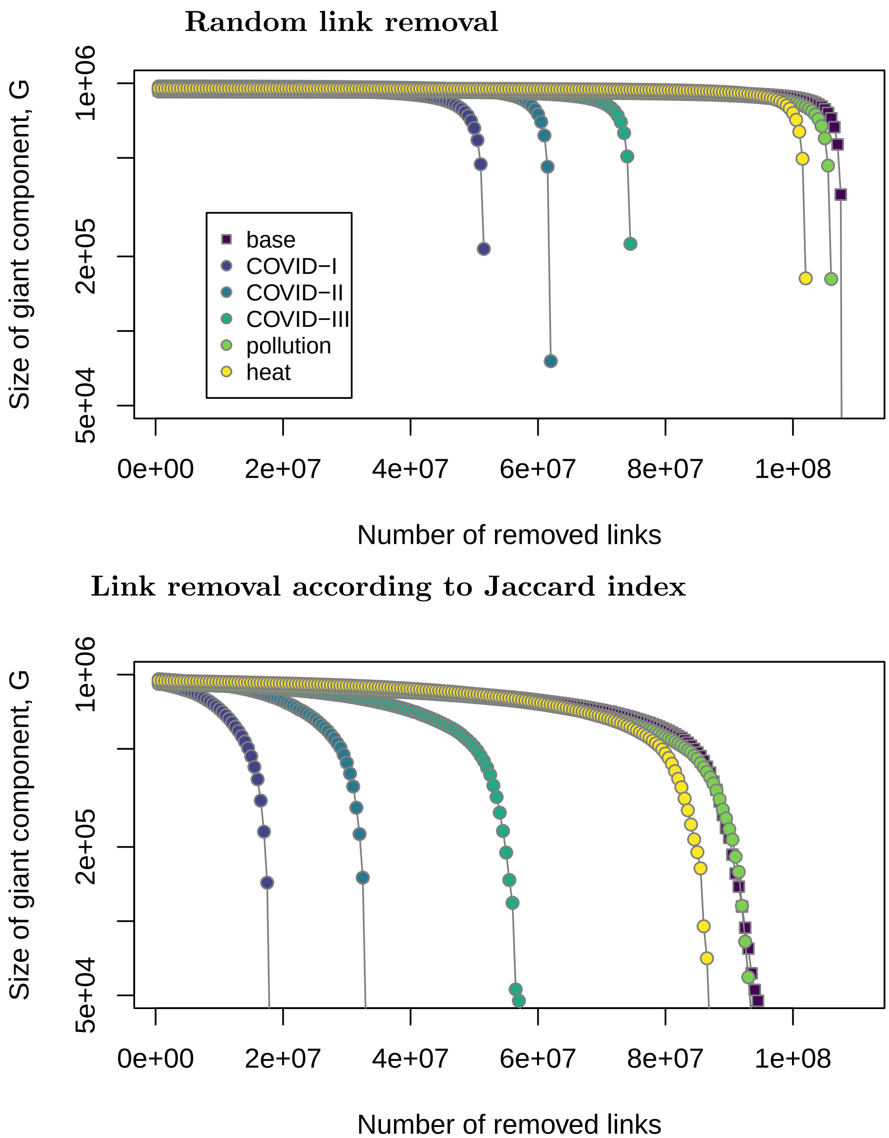

Figure 1: Quantifying the fragility of networks through percolation analysis. We measure the size of the largest component (largest number of connected nodes in the network), G, as a function of the number of progressively removed links. In a fragile network, the removal of a small number of links results into a complete fragmentation of the network ($G \approx 0$). Upper panel: random selection and removal of links. Lower panel: links are selected and removed according to their Jaccard index (links with low values of J_{ij} are removed first). Colours and symbols are as those in the upper panel.

increase the network fragility and reduce the spatial interactions between different population groups. For instance, one can expect that people form stronger local clusters during shocks due to reduced mobility across the city (i.e., they prefer to stay within their neighborhoods). This may lead to a disproportionate loss of weak ties that act as important bridges between tight-knit network communities.

To test this hypothesis, we calculate for each link $i \leftrightarrow j$ the Jaccard similarity coefficient, which quantifies the overlap of the common encounters of the two given individuals i and j. More precisely, for each link in the network the Jaccard coefficient is defined as (Leicht et al., 2006)

$$J_{ij}^{social} = \frac{n_{ij}}{k_i + k_j - n_{ij}}, \tag{1}$$

where n_{ij} is the number of common encounters of nodes i and j, and k_i (k_j) denotes the degree (number of links) of node i (j). If i and j have no common encounters, then we have $J_{ij} = 0$. If i and j are part of the same circle of spatial encounters, and $k_i = k_j = n_{ij}$ then $J_{ij} = 1$. In all other cases we get a value somewhere in between.

As such, links with high values of J_{ij} connect individuals *within* a tightly-knit circle of individuals, while links with low values of J_{ij} act as potential *bridges* between those communities (Onnela et al., 2007). Indeed, as depicted in the lower panel of Fig. 1, the targeted removal of these bridges (identified through low values of J_{ij}) leads to a much faster fragmentation of the interaction networks than the random removal of links. These bridges thus act as a 'glue' of the spatial interaction network. They also tend to be formed by more diverse individuals (compared to high-J_{ij} links within tight-knit groups), see Fig. A.3.

We contrast this to the spatial Jaccard:

$$J_{ij}^{spatial} = \frac{l_{ij}}{L_i + L_j - l_{ij}}, \tag{2}$$

where L_i and L_j are the distinct places an individual visits and l_{ij} are the common places i and j visit.

4 Shocks and urban social networks

In a first step we study how shocks affect exposure to diversity with regard to where people meet and with whom they meet. We base our results on a simple estimation equation:

$$Y_{i,t}^{l} = \gamma_i + \gamma_t + \beta T^{condition} + \epsilon_{i,t}, \tag{3}$$

where $Y_{i,t}$ represents either the log odds of meetings (extensive margin), the log number of meetings or the log average time spent per meeting (intensive margin). We denote the location of a meeting of individual i at time t. The superscript l can either refer to a specific place where co-location occurs or refer to overall (non-place specific) co-locations. The reference category is in each specification the "base Sunday" where we observe neither COVID-19 restrictions nor adverse environmental conditions. γ_i is an individual specific fixed effect capturing the overall meeting probability of an individual or – put differently, her overall mobility and social meeting behavior. In a next step, we zoom in on specific places and specific meeting partners to explore how individuals discriminate between meetings' partners and places during adverse conditions.

4.1 How do shocks affect *who* people meet?

We begin our analysis of the reactions of the Singaporean society to COVID-19 and environmental shocks first by investigating the strength of these shocks for the overall density of the network and second by examining the heterogeneous impacts of these shocks on different types of meeting ties. Table 1 is a general depiction of how shocks affect who people meet.

Overall, both COVID and environmental shocks lead to statistically significant, and large drops in the number of meetings individuals have compared to a standard base Sunday. This effect varies with the level of coordination in response to these shocks. For instance, in the first phase of the COVID-19 response (COVID 1), individuals met with 76.5% fewer people than on an average Sunday. This semi-elasticity falls to -49.9% on COVID 2 and -31.4% on COVID 3 when the Singaporean government lifted most pandemic-related restrictions. High pollution leads to a total decrease of 5.8% in the number of meetings, and high temperatures to a decrease of 3.1%. All coefficients are significant at the .001 level.

Table 1: How do shocks affect who people meet?

	Socio-demographic Indices							
	Overall		Same Ethnicity		Same Age		Same Home Area	
	Log Meetings	Log Avg. Time	Log Meetings	Log Avg. Time	Log Meetings	Log Avg. Time	Log Meetings	Log Avg. Time
Covid 1	-0.765***	0.906***	-0.744***	0.895***	-0.723***	0.877***	-0.341***	0.754***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid 2	-0.499***	0.581***	-0.491***	0.577***	-0.479***	0.567***	-0.195***	0.462***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid 3	-0.314***	0.279***	-0.312***	0.275***	-0.305***	0.269***	-0.104***	0.212***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High Poll.	-0.058***	-0.017***	-0.056***	-0.019***	-0.051***	-0.020***	-0.076***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High Temp.	-0.031***	-0.009***	-0.031***	-0.009***	-0.030***	-0.009***	-0.045***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	8,387,440	8,387,440	8,387,440	8,210,249	8,387,440	8,139,681	8,387,440	8,197,823
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.51	0.54	0.64	0.52	0.55	0.51	0.58	0.52

(i) Standard errors are clustered at the individual level and reported in parentheses $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. (ii) Each section reports both the log number of meetings and the log average time spent per meeting. The last two section focus on meetings with same demographics. (iii) E.g. Compared to a normal Sunday, *Covid 1* reduces total meetings by 76.5%, but, on average, each meeting lasts 90.6% longer.

The first lesson one may draw from such a table is that the semi-elasticities of environmental shocks are not as qualitatively small as expected. Indeed, the COVID pandemic responses provide us with an upper benchmark to assess the size of the response to environmental shocks and provide perspective. The response to high pollution is 18.5%(-.058/-.314) the size of the reaction to COVID 3, and 7.6% (-.058/-.765) the size of the reaction to COVID 1 – when meetings outside of the close family bubble were forbidden. Thus, these apparently smaller coefficients shall not be overlooked, given that the COVID pandemic is (hopefully) a once-in-a-century episode while high pollution occurs on a much more frequent basis.[4]

The second lesson is that people compensated for fewer meetings with longer meeting times during the pandemic. The average time spent per meeting increased even more during COVID 2 and 3 as the local authorities gradually lifted restrictive measures. This behavior is likely the translation of a catch-up effect whereby individuals would spend more time with acquaintances they were not allowed to meet in person during COVID 1. Generally, we understand the network responses during the pandemic as being driven by a regulated selection of meeting partners and locations, thus causing a behavioral reaction both to the shock (i.e., the virus circulation) and the regulation itself (i.e., home isolation). Absent such a regulation, individuals still meet less, but reductions in meeting times are much shorter – by 1.7% and 0.9% during the high pollution and high-temperature case, respectively.

[4]Between 2014 and 2021, Singapore suffered from 892 hours (i.e., 37.17 days) of high pollution with a Pollution Standard Index above 100 – considered unhealthy by the local authorities. Figure A.4 depicts the pollution time series.

The third lesson is that the intensity of the response to both COVID and environmental shocks was systematically lower when people share the same age or ethnicity than the average population result. While these semi-elasticities are statistically significantly different from the corresponding general responses to shocks, differences remain small compared to the size of the overall reaction. For instance, people only met 5.6% fewer individuals of the same ethnicity during high pollution, while they generally met 5.8% fewer people. This pattern holds for all shocks, seemingly indicating that people discriminate at the margin against meeting partners' demographics under adverse conditions. The same results hold regarding the average times per meeting. We observed the intensity of the response to both COVID and environmental shocks was systematically lower when people share the same age or ethnicity than the average population result. The differences in the effects are relatively small, and their direction may be mechanical: under fixed time endowment, clustering or co-locating with more people with similar social traits naturally implies spending less time with them, individually, on average. With regard to gender, we have estimated an analogous specification but do not find significant and qualitatively relevant differences.

Finally, while we do not observe that shocks cause a large social discrimination response, the results do indicate that they induce a significant spatial discrimination response. As expected, the impacts of the COVID shocks are much smaller for individuals sharing the same home area: they are reduced by 34.1% during COVID 1 for those with the same home area, compared to 76.5% for all individuals independent of their home area. However – perhaps, more interestingly, the impacts of environmental shocks are larger on meetings in the same home area: they are reduced by 7.6% during high pollution in the same home area, compared to 5.8% overall. Together, these results highlight that shocks cause a spatial reaction to the network: people do not meet at the same place as on a base day.

As has been argued above, individuals differ in many other attributes than age, ethnicity, gender, or home neighborhood which are relevant for the degree of mixing in city network but mostly unobservable. Therefore we follow a network-based definition of similarity between the two nodes of a tie. We compute for each tie the Jaccard similarity $J_{i,j}$ and evaluate the distribution of $J_{i,j}$ during different conditions as illustrated in Figure 2.

The figure shows that the distribution of the average Jaccard flattens with the intensity of the COVID shock relative to the base days (green lines). On the one hand, the distribution's

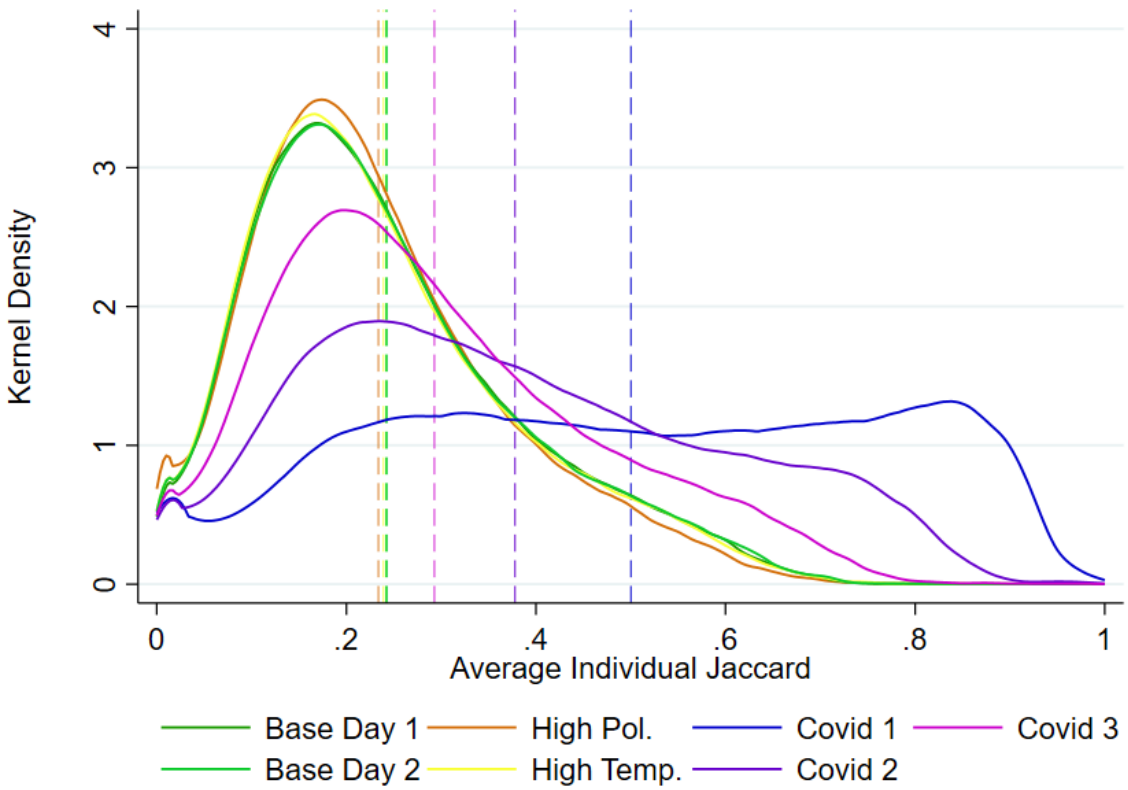

Figure 2: (i) Kernel density distributions of individual average Jaccard indices by type of shock. (ii) Dashed lines depict the distribution's mean. (iii) Conditional on meeting, on average individual meet with more partners having a similar network during COVID-19 shocks, but meet with are exposed to more population diversity during high pollution and high temperature. shocks

right tail becomes significantly thicker, indicating that individuals tended to meet significantly more with people sharing the same sub-network during the pandemic. On the other hand, the left part of the distribution got significantly thinner, indicating that people met significantly less with individuals sharing different sub-networks, hence drawing fewer 'bridges' and fragilizing the network. In other words, during COVID and because of the subsequent meeting restrictions, not only did individuals meet less, but the city network collapsed into many urban 'villages' defined by local close-ties clusters.

However, this statement is challenged by changes in the average Jaccards' distribution during environmental shocks, during which individuals can select meeting partners and meeting places regardless of any regulation. Indeed, during unconstrained mobility shocks – high pollution and high temperatures – the Jaccard distribution remains very close to the Jaccard distribution during base days. This may indicate that individuals use spatial mobility to smoothen the impact of shocks on their interactions.

A closer look at the Appendix Table A 2 confirms that, during the pandemic, individuals encountered many more acquaintances with overlapping networks (+42% increase in Jaccard index during COVID 1) and spent much more time with the high Jaccard contacts which we refer to as close ties (+207.8% during COVID 1). Respectively, the pandemic seriously harmed bridge creation (-116.8% low-Jaccard meetings and -106.4% average time per meeting during COVID 1). Therefore, not only did the pandemic reduce the total number of meetings (see Table 1), but it also affected the structure of the urban social network. Environmental shocks also negatively affected the number of meetings displaying low Jaccard indices. Individuals encountered much fewer acquaintances with bridges (-7.4% decrease in Jaccard index during high pollution). But, contrary to the COVID shocks, they also reduced meetings with overlapping networks (-4.9% decrease in Jaccard index during high pollution). In other words, all shocks affect bridge creation, but unconstrained mobility shocks also reduce the number of close ties. Therefore, the latter's impact on the average Jaccard is quasi-null (-0.8 percentage points during high-pollution and -0.3 percentage points during high-temperature shocks). In contrast, it is strongly positive when individuals' mobility is constrained (+25.7 percentage points during COVID 1).

To rationalize this result, we bring up the role of place selection. Network interactions are drawn between different individuals, often originating from the same social background.

At the extensive margin, these interactions' existence depends on the diversity of places' amenities. For instance, meeting during high pollution episodes is highly costly in the absence of indoor meeting places. Likewise, meeting during a pandemic is very expensive without outdoor spaces. Conditional on places' diversity, individuals' spatial mobility conditions the network's structure. In other words, individuals can use mobility to smoothen shocks on their social network once provided with possible meeting locations.

4.2 How do shocks affect *where* people meet?

Table 2 describes the general meeting patterns for different locations. For each location, the first column reports how shocks impact the odds of meeting with at least one individual – i.e., meetings at the extensive margin, and the other two columns report how the shocks impact the number and duration of meetings – i.e., meetings at the intensive margin.

These results illustrate how shocks affect location preferences and, in doing so, how they condition where people meet. Shocks affect choices for meeting location (and transportation to that location) either through regulation (e.g., during COVID) or selection (e.g., during high pollution). For instance, high pollution makes walking and outdoor spaces less attractive. A fast-spreading virus causes underground transportation and clubbing to be less attractive. Raw distance costs are time-invariant and, assuming that individuals do not change home location, are entirely absorbed by individual fixed effects.

First and foremost, note that all shocks systematically reduce the odds of meetings in all locations. This is consistent with the results in Table 1 and is indicative that a non-negligible share of individuals responds to adverse conditions by not meeting at all – i.e., they leave the (presential) network. Interestingly, these extensive margin responses to the shocks are the largest and the smallest in the Downtown area – where indoor interactions are the most likely – for COVID 1 and Pollution, respectively. In the first case, indoor interactions come at high risk, while in the second case, they may reduce the adverse effects of pollution.

The first set of results in Table 2 describes how individuals sort between their home and not home neighborhood. The impact on location preferences by distance from home is striking. An order of magnitude separates the pandemics' impact on the odds of meeting in the home neighborhood compared to a different area. During COVID 1, the odds of meeting

Table 2: How do shocks affect network formation in space?

	Ext. margin	Int. margin		Ext. margin	Int. margin	
	Log Odds Visit	Log Meetings	Log Avg. Time	Log Odds Visit	Log Meetings	Log Avg. Time
	HOME AREA			NOT HOME AREA		
Covid 1	-0.204***	-0.361***	0.735***	-2.271***	-0.798***	0.040***
	(0.005)	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)
Covid 3	-0.383***	-0.121***	0.201***	-0.945***	-0.379***	0.020***
	(0.005)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)
High Poll.	-0.350***	-0.049***	0.023***	-0.104***	0.071***	-0.011***
	(0.005)	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)
Observations	1,521,236	3,584,086	3,584,086	2,896,896	1,491,137	1,491,137
Individual FE	Y	Y	Y	Y	Y	Y
R^2	–	0.68	0.57	–	0.58	0.55
χ^2	8,495.33	–	–	510,432.09	–	–
	MOST FREQUENTED			LEAST FREQUENTED		
Covid 1	-1.411***	-0.585***	0.685***	-1.176***	0.073***	0.353***
	(0.004)	(0.002)	(0.001)	(0.012)	(0.015)	(0.012)
Covid 3	-0.843***	-0.279***	0.174***	-0.610***	-0.087***	0.089***
	(0.004)	(0.002)	(0.001)	(0.011)	(0.015)	(0.011)
High Poll.	-0.198***	-0.069***	0.015***	-0.161***	0.054***	-0.051***
	(0.004)	(0.002)	(0.001)	(0.010)	(0.013)	(0.010)
Observations	1,865,776	1,849,154	1,849,154	244,920	45,766	45,766
Individual FE	Y	Y	Y	Y	Y	Y
R^2	–	0.65	0.72	–	0.71	0.74
χ^2	141353.80	–	–	11593.77	–	–
	DOWNTOWN			PARKS		
Covid 1	-2.915***	-1.200***	0.362***	-1.133***	-0.307***	0.350***
	(0.018)	(0.029)	(0.012)	(0.012)	(0.019)	(0.013)
Covid 3	-1.246***	-0.746***	0.078***	-0.424***	-0.168***	0.091***
	(0.010)	(0.021)	(0.008)	(0.010)	(0.017)	(0.012)
High Poll.	-0.027***	-0.033**	-0.008	-0.283***	-0.235***	-0.056***
	(0.007)	(0.015)	(0.006)	(0.010)	(0.017)	(0.012)
Observations	384,100	40,507	40,507	262,444	31,393	31,393
Individual FE	Y	Y	Y	Y	Y	Y
R^2	–	0.76	0.71	–	0.71	0.70
χ^2	70089.39	–	–	9820.68	–	–

(i) Standard errors reported in parentheses $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. (ii) *Most Frequented* and *Least Frequented* correspond to the top and bottom 25% places in terms of co-location density, respectively (iii) Extensive (Intensive) margin of visits follows a logistic (OLS) specification. (iv) In particular, columns 1 and 4 report the Log Odds Ratio (p/1-p) of visits. (v) E.g. Compared to a normal Sunday, *Covid 1* reduces the odds of meeting *in general* in *Not Home Area* by 227%. Moreover, conditional meeting in *Not Home Area*, an individual would meet on average 79.8% less people but spend 4% more time with them.

in the home neighborhood were down by 20.4% compared to a base Sunday. During the same period, the odds of meeting in a different area were down by 227.1% compared to a base Sunday. Conditional on visits, people would meet 36.1% fewer acquaintances in the home neighborhood during COVID 1, compared to 79.8% fewer acquaintances in a different area. Conditional on meeting with these acquaintances, people would spend 73.5% more time in the home neighborhood during COVID 1, compared to 4% more time in a different area. Hence, the compensation via meeting time during COVID mainly occurs in the home location. Mobility restrictions imposed during the phases of the pandemics clearly drive these effects. However, during high pollution, the odds of meeting in the home neighborhood were down by 35% compared to a base Sunday. During the same period, the odds of meeting in a different area were only down by 10.4%. Similarly, conditional on visits, people would meet 4.9% fewer acquaintances in the home neighborhood during high pollution but 7.1% more acquaintances in a different area. This set of results already suggests that individuals adapt their mobility patterns in response to the changes in location opportunities caused by shocks both in the COVID and in the polluted environment.

The second set of results in Table 2 describes how individuals sort between the most and least frequented places on a base Sunday. Each category corresponds to the top and bottom quartiles in the co-location density distribution on a base Sunday, respectively. At the extensive margin, shocks more severely affect the chances of meeting in the most frequented areas than in the least frequented areas. The odds of visits are down by 141.1% in the most frequented areas and 117.6% in the least frequented ones during COVID 1. They decreased by 19.8% in the most frequented areas and 16.1% in the least frequented ones during high pollution. However, conditional on a visit, the intensity of the meeting response was systematically significantly smaller in the most frequented areas compared to the least frequented areas. For instance, conditional on a visit, individuals would meet 58.5% fewer individuals in the most frequented areas during COVID 1 but 7.3% more individuals in the least frequented ones. They would meet 27.9% fewer individuals in the most frequented areas during COVID 3 but 8.7% fewer individuals in the least frequented ones. They would meet 6.9% fewer individuals in the most frequented areas during COVID 3 but 5.4% more individuals in the least frequented ones. Almost mechanically, the intensity of the response in the time spent per meeting was significantly larger in the most frequented areas than in the least frequented areas. These results could indicate that individuals respond to adverse conditions by favoring places with lower co-location density during the pandemic and the high pollution days. In other words, people react at the intensive margin by meeting in locations where individuals' concentration is lower, hence likely to be less polluted and where a virus spreads less quickly.

Finally, the third set of results in Table 2 illustrates how places' characteristics matter for individuals sorting. On the one hand, the Singapore Downtown area is a highly developed location, featuring many indoor meeting spaces. Shopping malls and restaurants in the Downtown area are very popular places on a base Sunday, as illustrated in Figure A.1. On the other hand, parks are urban elements designed to provide outdoor meeting locations and environmental amenities to individuals living in urban environments. At the extensive margin, people would reduce more visits to the Downtown area (-291.5% - -124.6%) than to parks (- 113.3% - -42.4%) during the pandemic. Respectively, they would reduce more visits to the parks (-28.3%) than to the Downtown (-2.7%) area during the high pollution. The same patterns are present at the intensive margin of meetings as well. Conditional on visits, people would reduce the number of meetings in the Downtown area (-120% - -74.6%) more than to parks (- 30.7% - -16.8%) during the pandemic. Respectively, they would reduce more meetings to the parks (-23.5%) than to the Downtown (-3.3%) area during the high pollution. During the pandemic, individuals compensated for fewer meetings with longer meeting times, whereas individuals would have shorter meetings outside during high pollution. Overall, nearby outdoor areas are relatively favored during COVID, whereas indoor areas are relatively favored during high pollution. Places' characteristics condition individuals' meeting possibilities. More generally, individuals discriminate against places deemed riskier concerning local environmental conditions.

In conditioning people's mobility through regulation or meeting place selection, shocks affect population mixing. The regulatory measures in response to the COVID pandemic are an extreme example of such a statement. During that time, individuals mostly interact in their home area, which constraints most interactions with neighbors, who are likely to belong to the same network cluster. However, when high pollution reduces the possibility of meeting in open spaces, people wishing to leave their home area will likely converge to indoor areas – bars, malls, theaters, etc. In the next section, we explore how shocks then affect the creation of bridges, which are crucial for urban network stability, as illustrated in section 3.

4.3 How do shocks affect *mixing* in space?

Section 4.1 documented how individuals reduced encounters but did not necessarily discriminate against meeting partners based on social homophily. Constrained mobility shocks encourage meeting with individuals belonging to the same cluster, whereas mobility was used to smooth the impact of uncoordinated shocks on the network's structure. However, section 4.2, however, illustrated that shocks induce people to discriminate against meeting locations' characteristics. Table 3 now shows how shocks impact the mixing patterns in space as measured by the Jaccard indices at different places.

Table 3: Aggregate effect of shocks on social mixing by location

	Home	Not Home	Most Freq.	Least Freq.	Downtown	Parks
	$\mu = .224$	$\mu = .144$	$\mu = .216$	$\mu = .088$	$\mu = .148$	$\mu = .06$
	$\sigma = .118$	$\sigma = .156$	$\sigma = .135$	$\sigma = .029$	$\sigma = .138$	$\sigma = .085$
Covid 1	0.278***	0.044***	0.243***	0.149***	0.049***	0.071***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Covid 3	0.063***	0.006***	0.041***	0.030***	-0.014***	0.013***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)
High Poll.	-0.007***	0.002***	-0.007***	-0.001	-0.003**	-0.014***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)
Observations	3,584,086	1,491,137	1,849,154	45,766	40,507	31,393
Individual FE	Y	Y	Y	Y	Y	Y
R^2	0.65	0.49	0.66	0.66	0.69	0.64

(i) Standard errors reported in parentheses $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. (ii) Dependent variable is the individual average Jaccard Index per individual, day, and location (iii) *Most Frequented* and *Least Frequented* correspond to the top and bottom 25% places in terms of co-location density, respectively (iv) Descriptive statistics μ and σ correspond to the mean and standard deviation of the dependant variable on a base Sunday (v) E.g., *Covid 1* increased the average individual Jaccard by 27.8 percentage-point compared to the Base Sunday in home locations, i.e., an increase of 124.1% (.278/.224) of the mean average individual Jaccard on that base day in home locations.

The two places where people mix relatively little on a base Sunday are the home location and most frequented areas. Both locations display about 22% of network overlap among ties on a base Sunday. People tend to meet more people sharing a different network in Parks and Downtown, or the least frequented areas where the average Jaccard indices are 0.06, 0.148, and 0.088, respectively.

During the pandemic, people almost always met more with individuals sharing the same network than during this base Sunday. Unsurprisingly, the absolute effect is the largest in COVID 1 in the Home area, with a 27.8 %-point increase. In relative terms, the effect was the strongest during COVID 1 in the least frequented areas. Generally, the pandemic caused people to meet relatively more with individuals sharing the same network in the Home area than in the Not-Home area, in the least frequented than in the most frequented areas, and in parks more than in the downtown area. These favored places – nearby home, less frequented, outdoor areas – were also favored regarding the number of meetings during the pandemic. In light of the results of Section 4.2, we see that people favored meetings in these places, but they particularly favored meetings with close ties in these places. These locations were considered (by regulation or selection) to be less risky for contamination during the pandemic, and the preferences shifted towards meetings with close ties.

Contrary to the pandemic effect, people almost always meet more with individuals sharing a distinct network during high pollution when considering specific places except for the not-home area. The impact of high pollution on the Jaccard distribution is also much milder, at most of -1.4%-point in parks. This latter mild reduction is likely explained by the absence of mobility regulation, allowing people to sort freely in space. It is easier to smooth the shock when people can freely discriminate who and where to meet. Interestingly, the relative decrease in Jaccard value in parks during high pollution is substantial (considering an average of 0.06, we observe a reduction of about 25 percent). This may be explained by parks being unpopular meeting locations during pollution, especially for *coordinated*, close-tie meetings, thus leading to a faster decrease in close ties meetings than in bridge meetings there.

This important pattern is highlighted in the Appendix Table A 3: during high pollution, the average Jaccard did not increase in most places because people were actively meeting with more bridges, but also because they met much less – if they met at all – with their close ties, especially in places deemed as unpleasant. In general, during high pollution, the number of meetings with close ties dropped everywhere, particularly in unpleasant areas, and proportionally more than the number of meetings with bridges. In parks, high pollution caused the number of meetings with close ties to decrease by 14.8%, while meetings with bridges decreased by 10.4%. However, in most places, the number of bridges even increased. There are several possible explanations for this. The most straightforward rationale to explain this general pattern is that when close, central, intertwined ties leave the network, the remaining surrounding ties' Jaccard index mechanically decreases, and these remaining ties become bridges. If the shocks remove primarily close ties meetings, the overall network will be naturally more mixed. Another possibility, which would require highly local data about meeting location characteristics, is that bridges are created as shocks limit location possibilities to fewer, safer spots and push diverse, close ties networks to co-locate in the same area. For instance, friends from different parts of the city converge in the same malls because of high pollution. Still, these passive bridge creation processes appear to be consistently smaller in magnitude than the initial, active close ties loss.

Therefore, when mobility is unconstrained, adverse conditions primarily affect the volume of meetings with close ties and the meeting locations of close ties. Places characteristics might help smooth the shock on close ties interactions, and close ties use then these areas to meet. In the case of high pollution, this combined effect caused people to decrease relatively less their average Jaccard in the not-home area than in the home area, in the least frequented than in the most frequented areas, and in the Downtown area more than in Parks. The network also favored nearby not-home, less frequented, indoor areas during high pollution.

During the COVID pandemic, bridges decreased more than close ties as regulation required individuals to remain physically close to their families and friends. In doing so, the city network crumpled into many small 'villages.' Nonetheless, when mobility is unconstrained, as is the case during high pollution, the networks' close ties may collapse before the bridges as individuals limit meeting with their close ones, especially in risky or unattractive areas, thus making the remaining encounters crucial for the network's very existence.

5 Discussion

In our setting, shocks affect the attractiveness of different places or, put differently, the costs of visiting specific places and – in particular, the COVID shock – constrain mobility. The previous results indicate that individuals react to shocks in the following ways: i) at the extensive margin by reducing the number of meetings, ii) by using mobility and the choice of meeting locations to minimize the costs of a meeting, or iii) at the intensive margin by adjusting the meeting times. One could formalize this idea through a simple constraint function: given a shock, is there a place whose characteristics allow me to meet a close tie safely? Can my close relation and I reach this place? If not, then we cannot meet. Mobility and constraint choice of meeting place thereby affect the type of meetings and network structure.

The variety and distances between places in Singapore arguably did not change between September 2019 and June 2020. The shocks – COVID, high pollution, and high temperatures, affected meetings through two dimensions. First, they heterogeneously impacted the value of meetings by location: pollution positively affected individuals' preferences for indoor spaces over outdoor spaces, whereas COVID negatively affected these individuals' preferences. Second, the shocks affected mobility restrictions differently. Uncoordinated shocks, i.e., pollution and high temperatures, did not restrict mobility per se, whereas the pandemic required individuals to stay within their home clusters.

With this in mind, a couple of comments are of interest. First, this current version of the paper does not directly account for spatial mobility. Instead, we explore reactions to shocks as variations in co-location patterns in different types of meeting places. Doing so allowed us to confirm that shocks heterogeneously impacted the value of meetings by location but left aside the second channel through which shocks affect meetings: mobility. In an upcoming version, we directly tackle the constraint function mentioned above by deriving a spatial Jaccard index – a measure of overlapping visited areas, as a proxy for overlapping tie mobility. We then use this new measure to study how shocks affect whether people meet and whom they meet – i.e., the impact of the spatial Jaccard index on the social Jaccard index.

Second, this first version clearly illustrates how changing meeting conditions affect meeting at the extensive margin. The results indicate that the overall number of meetings decreases for all types of shocks. Yet, the current data does not allow us to analyze whether these meetings, which would have otherwise existed absent the shock, are shifted to the digital space. In other words, we are currently ignorant of the true number of meetings that disappear from the network as we do not know to what extent individuals smooth shocks using the digital space. Importantly, the digital space typically does not allow creating new ties – one usually meets online with people she already knows. Consequently, smoothing shocks with the digital space, rather than mobility in the physical space, which allows meeting new people, may have significant consequences on the structure of the urban social network. In particular, the unplanned meetings with individuals sharing a small overlap in their network will vanish. In a related paper, we study the impact of shocks on the marginal rate of substitution between the physical and digital space by adding the internet, social apps, and phone consumption to the current data.

6 Conclusion

Social interactions are critical to creating, diffusing, and conserving social and human capital. Spatial proximity – and therefore urban density– strengthen this relation, making social interactions fundamental for cities. With more than 80% of the developed countries population living in urban areas and rapid urbanization in developing ones, more frequent and intense environmental shocks might affect many of these benefits from density.

This paper aims to document the impact of such adverse conditions – i.e., heat, pollution, and COVID-19, on the patterns of urban social interactions. Using a unique, high-resolution dataset on mobility and meetings covering half of the population in Singapore, we stress the importance of meeting location diversity to mitigate the impact of adverse environmental shocks on the network of urban social interactions.

We first characterize the network and sociodemographic characteristics of social ties bridging the network's clusters together. We then show that these ties, characterized by a higher diversity, are particularly sensitive to shocks. Overall, environmental shocks decrease the total number of meetings (by 77% in the worst COVID case and by 7% during high pollution). However, environmental conditions also affect preferences over meeting locations. Conditional on meeting, an environmental shock may increase population mixing by constraining meeting location preferences. Here, we bring to light a trade-off: when a negative shock occurs, higher places' diversity increases meeting possibilities but decreases mixing opportunities. Respectively, lower places' diversity decreases meeting possibilities but increases mixing opportunities.

Meeting places diversity, therefore, plays a crucial role in keeping the city network from collapsing into a multitude of independent clusters (or 'villages') when a shock occurs, which underlines the importance of sound urban planning for city networks' resilience to adverse conditions.

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APPENDIX

Table A 1: Base Sunday Descriptive Statistics

Location	Total Encounters	Meetings μ	Meetings σ	Time μ	Time σ	Jaccard μ	Jaccard σ
Overall	110,567,516	115.57	169.62	255.63	171.03	.241	.141
By Residence:							
- *Home*	66,998,396	72.75	104.74	306.01	176.48	.224	.161
- *Not Home*	43,569,120	46.99	123.14	81.92	86.82	.104	.161
By Popularity:							
- *Most Freq.*	58,667,639	95.42	165.11	231.778	187.01	.216	.156
- *Least Freq.*	482,072	15.77	34.31	168.02	193.35	.088	.135
By Type:							
- *Downtown*	6,258,826	127.69	269.14	59.09	42.04	.148	.139
- *Parks*	1,702,384	40.85	65.14	143.67	144.21	.067	.085

(i) All statistics are provided on a base Sunday (ii) Base Sunday for Parks differs from Base Sunday for other locations (iii) Statistics μ and σ are at the individual level (iv) *Total encounters* refers to the total number of bi-lateral meetings $\{i; j\}$ $\{j; i\}$ occurring in a given area (v) *Most Freq.* and *Least Freq.* refer to the 25% most and least frequented planning areas, as defined by the total number of bi-lateral meetings occurring per square kilometer during a Base Day (vi) E.g. The average meeting time out of home area is 82 minutes on a Base Sunday.

Table A 2: Aggregate effect of shocks on social mixing

	Jaccard Indices					
	Average	Median	Bottom 25% (bridges)		Top 25% (close ties)	
	($\mu = .243$; $\sigma = .143$)	($\mu = .228$; $\sigma = .156$)	Log Meetings	Log Avg. Time	Log Meetings	Log Avg. Time
Covid 1	0.257***	0.307***	-1.168***	-1.064***	0.420***	2.078***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.003)
Covid 2	0.136***	0.144***	-0.916***	-0.810***	0.329***	1.381***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.003)
Covid 3	0.052***	0.051***	-0.589***	-0.360***	0.145***	0.667***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.003)
High Poll.	-0.008***	-0.016***	-0.074***	0.072***	-0.049***	-0.038***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.003)
High Temp.	-0.003***	-0.003***	-0.107***	-0.055***	-0.024***	-0.015***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	6,387,240	6,387,240	8,387,440	6,387,240	8,387,440	6,387,240
Individual FE	Y	Y	Y	Y	Y	Y
R^2	0.54	0.53	0.67	0.55	0.62	0.51

(i) Standard errors are clustered at the individual level and reported in parentheses $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. (ii) Column (1) reports the impact of shocks on the average Jaccard. The mean and standard deviation on the base day are reported. (iii) Column (2-3) and (4-5) report respectively the impact of shocks on high and low Jaccard encounters as defined on a base day.

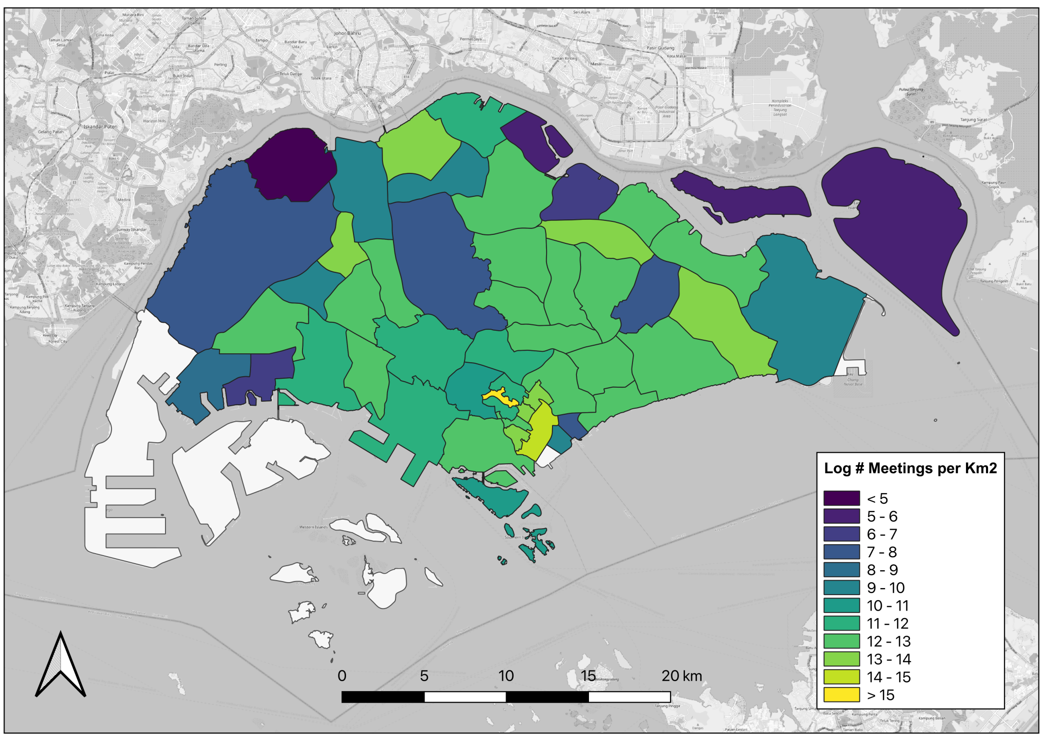

Figure A.1: Log density of individual meetings per planning area on a base Sunday. There are 55 planing areas in Singapore. We collect information on 51 of them. The four areas left (uncolored) are Tuas, Western Islands, Straits View, and Changi Bay. These are mostly industrial, unpopulated regions. In general, more than 2.1 million individual meetings occur in the average planning area on a Base Sunday. The Orchard planning area – notable for its many commercial centers – displays the highest meeting density with close to 5.2 million individual meetings.

Table A 3: How do shocks affect bridges vs. close ties meetings in space?

	Bridges	Close Ties	Bridges	Close Ties
	HOME AREA		NOT HOME AREA	
Covid 1	-0.911***	0.436***	-0.703***	0.199***
	(0.002)	(0.002)	(0.003)	(0.012)
Covid 3	-0.378***	0.090***	-0.353***	-0.070***
	(0.001)	(0.003)	(0.002)	(0.009)
High Poll.	0.041***	-0.140***	0.038***	0.054***
	(0.001)	(0.003)	(0.002)	(0.008)
Observations	2,365,366	2,181,757	1,163,234	258,191
Individual FE	Y	Y	Y	Y
R^2	0.59	0.60	0.60	0.57
	MOST FREQUENTED		LEAST FREQUENTED	
Covid 1	-0.952***	0.297***	-0.434***	0.922***
	(0.003)	(0.004)	(0.014)	(0.044)
Covid 3	-0.401***	-0.014***	-0.205***	0.220***
	(0.002)	(0.004)	(0.012)	(0.045)
High Poll.	0.022***	-0.123***	0.049***	-0.101**
	(0.002)	(0.004)	(0.010)	(0.047)
Observations	1,279,181	1,075,701	35,379	6,830
Individual FE	Y	Y	Y	Y
R^2	0.60	0.58	0.59	0.71
	DOWNTOWN		PARKS	
Covid 1	-1.018***	-0.510***	-0.613***	0.464***
	(0.023)	(0.067)	(0.016)	(0.060)
Covid 3	-0.491***	-0.845***	-0.308***	0.070
	(0.016)	(0.051)	(0.014)	(0.060)
High Poll.	0.010	-0.232***	-0.104***	-0.148**
	(0.012)	(0.029)	(0.014)	(0.067)
Observations	27,869	9,797	26,570	2,777
Individual FE	Y	Y	Y	Y
R^2	0.67	0.78	0.63	0.64

(i) Standard errors reported in parentheses $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. (ii) *Bridges* refers to the Log number of meetings whose Jaccard index belongs to the first quartile of the Jaccard distribution on a base Sunday (iii) *Close Ties* refers to the Log number of meetings whose Jaccard index belongs to the fourth quartile of the Jaccard distribution on a base Sunday (iv) E.g. Compared to a normal Sunday, *Covid 1* reduces the number of meetings with bridges by 91.1% in the Home area.

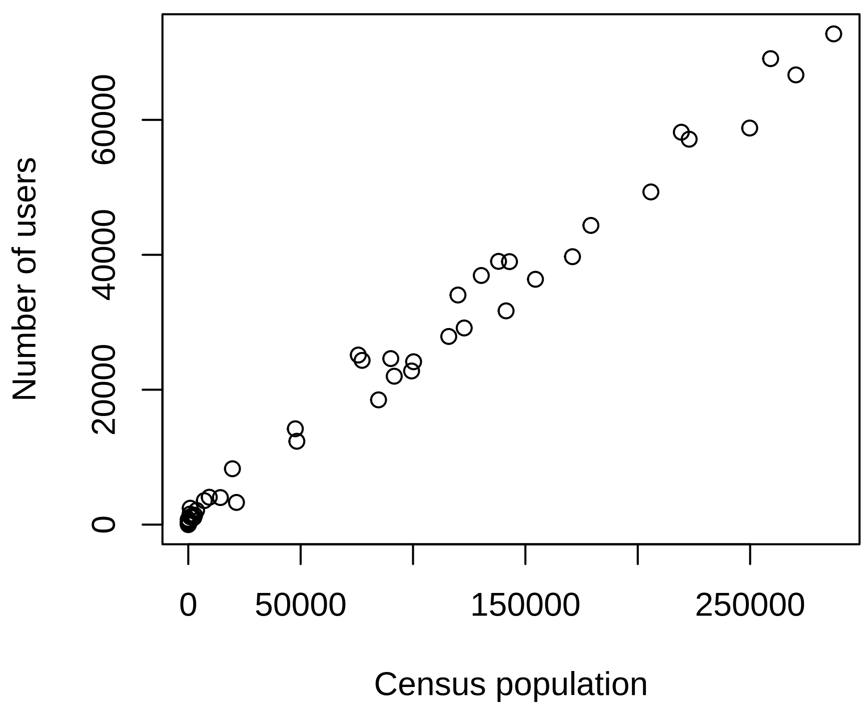

Figure A.2: Number of mobile phone users assigned to each planning area in Singapore versus census population size.

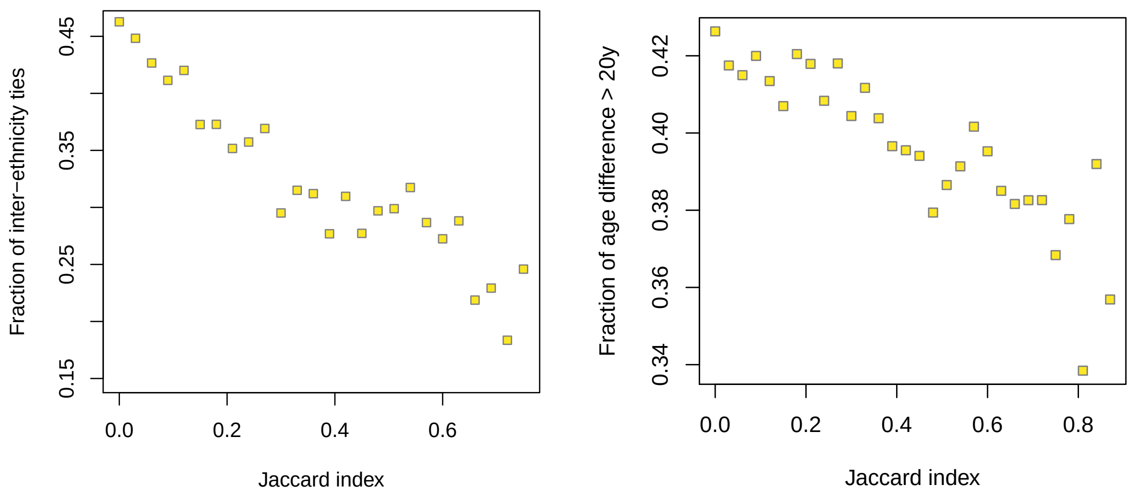

Figure A.3: Left: the fraction of inter-ethnicity ties to all ties with a given value of the Jaccard index, J_{ij}, decreases with increasing value of J_{ij}. Hence, low-J_{ij} links tend to be more frequently formed by individuals of different ethnicities (compared to high-J_{ij} links). Right: the fraction of ties between two individuals with age difference > 20 years decreases with increasing value J_{ij}. Hence, low-J_{ij} links tend to be more frequently formed by two individuals with a larger age difference (compared to high-J_{ij} links).

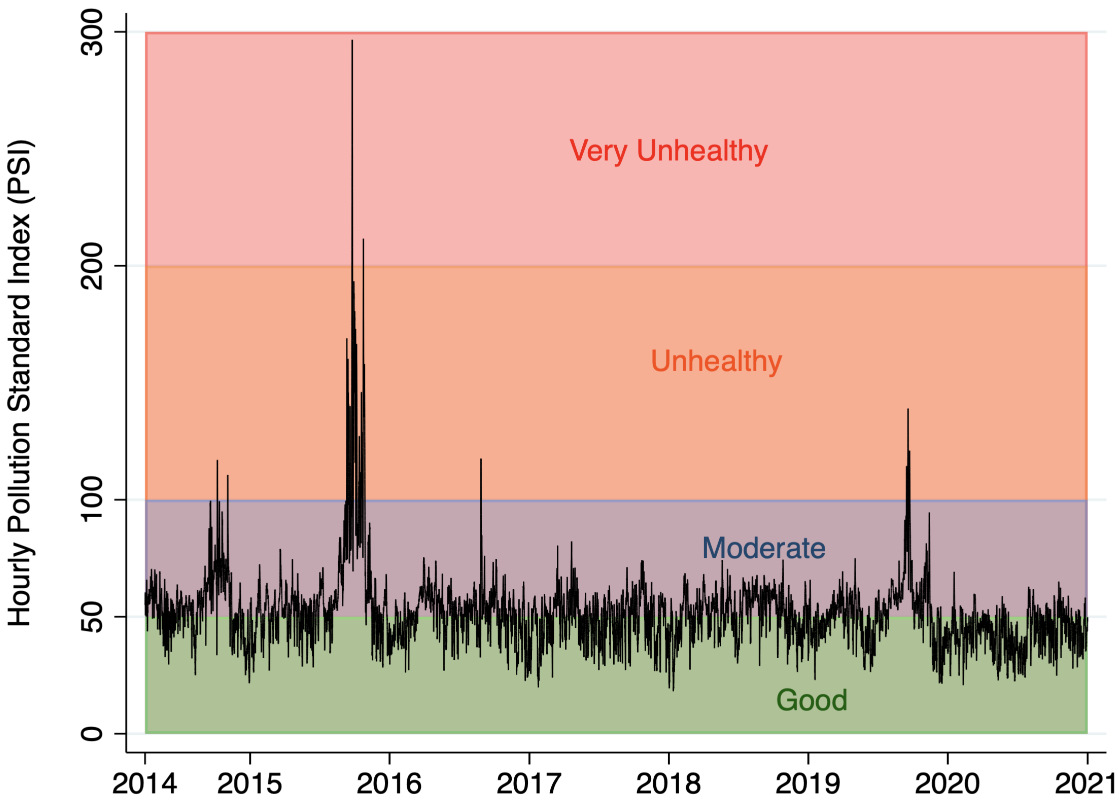

Figure A.4: (i) Hourly Standard Pollution Index (PSI) time series is superimposed on the levels of health advisories. (ii) The components entering the PSI index are particulate matter (PM 10), fine particulate matter (PM 2.5), sulphur dioxide (SO 2), nitrogen dioxide (NO 2), ozone (O 3), and carbon monoxide (CO). (iii) *Good* & *Moderate*: All persons can perform normal activities (iv) *Unhealthy*: Healthy person must reduce outdoor activities. Pregnant and elderly person must minimize them. People subject to lung or heart disease must avoid them. (v) *Very Unhealthy*: People must avoid outdoor activities. (vi) Source: Singapore National Environment Agency

Center for Regional Economic Development (CRED)

University of Bern

Schanzeneckstrasse 1

P.O.Box

CH-3001 Bern

Telephone: +41 31 684 37 11

E-Mail: info@cred.unibe.ch

Website: http://www.cred.unibe.ch

The Center for Regional Economic Development (CRED) is an interdisciplinary hub for the scientific analysis of questions of regional economic development. The Center encompasses an association of scientists dedicated to examining regional development from an economic, geographic and business perspective.

Contact of the authors:

Pierre Magontier

University of Bern, CRED

Schanzeneckstrasse 1 / P.O.Box, CH-3001 Bern

Telephone: +41 31 684 49 97

Email: pierre.magontier@unibe.ch

and Universitat de Barcelona

Barcelona Institute of Economics

C/ John M. Keynes, 1-11, ESP-08034 Barcelona

Maximilian von Ehrlich

University of Bern, CRED

Schanzeneckstrasse 1

P.O.Box

CH-3001 Bern

Telephone: +41 31 684 80 75

Email: maximilian.vonehrlich@unibe.ch

Markus Schläpfer

University of Bern, CRED

Schanzeneckstrasse 1 / P.O.Box, CH-3001 Bern

Telephone: +41 31 684 37 11

Email: markus.schlaepfer@unibe.ch

and Nanyang Technological University, NTU

50 Nanyang Ave

Singapur 639798