Production disruptions from social distancing

Miklós Koren[1,2,3◕¤*], Rita Pető[2‡]

1 Central European University, Budapest, Hungary
2 KRTK KTI, Budapest, Hungary
3 CEPR, London, UK

◕This author is responsible for the research idea, the theoretical model, and the analysis of the spatial data. Both authors contributed equally to reviewing the analysis results and writing the manuscript.
‡This author is responsible for the analysis of the occupation data. Both authors contributed equally to reviewing the analysis results and writing the manuscript.
¤Current Address: Central European University, Nádor u. 9., 1051 Budapest, Hungary
* korenm@ceu.edu

Abstract

Social distancing interventions can be effective against epidemics, but may disrupt production in businesses that rely heavily on face-to-face communication. We develop a model of communication and production to study the effects of a policy that poses limits on worker interaction. This policy disrupts businesses with strong division of labor (and hence high need for communication) and those that are located in urban centers with high population density. We measure the prevalence of communication-related tasks and the urban density of workers for each detailed industry in the U.S. We predict that schools, grocery stores, and banks will suffer the biggest disruptions in response to the 2019–20 coronavirus pandemic. Overall, 22.9 million people work in the ten most affected industries.

Introduction

Social distancing measures are effective non-pharmaceutical interventions against the rapid spread of epidemics [1–4]. Many countries have implemented or are considering measures such as school closures, prohibition of large gatherings and restrictions on transportation to slow down the spread of the 2019–20 coronavirus pandemic [5, 6]. What are the economic effects of such social distancing interventions? Which businesses are most affected by the restrictions?

Past research has analyzed the efficacy of social distancing interventions on reducing the spread of epidemics using the 1918 Spanish Flu in the U.S. [1–3] and seasonal viral infections in France [7]. Our knowledge of economic impacts, however, is limited. For this question, the case of the Spanish Flu pandemic is less relevant, as the importance of face-to-face communication has increased in the last 100 years through urbanization [8, 9] and specialization increased in business services as well [10, 11]. This paper formalizes the idea, suggested by casual evidence, that many urban service sectors rely heavily on face-to-face communication.

We build a model of communication within the production process to understand how limiting face-to-face interaction increases costs. Without social distancing, workers specialize in a narrow range of tasks and interact with other workers completing other tasks. This division of labor reduces production costs but requires frequent contact between workers. In the model, the number of contacts per worker is the most frequent in high-population-density areas in businesses where the division of labor is important. When face-to-face interaction is limited, these are exactly the businesses that suffer the largest cost increases. Our model can also explain when telecommunication is a low-cost substitute for face-to-face interaction.

To measure production disruptions from social distancing, we turn to recent data on the task descriptions of each occupation [12] and the precise geographic location of non-farm businesses in the U.S. [13]. Some occupations require frequent communication with others (inside or outside the firm). The most communication-intensive occupations include health care professionals, teachers, and managers. And some sectors employ most of their workers in ZIP-code areas with high population density. The highest-density sectors are apparel manufacturing, information and business services, and performing arts. Both measures are necessary to understand exposure to social distancing. Firms may also locate in urban centers to minimize shipping costs with respect to suppliers and customers [14]. But if they also have a high prevalence of communication-related tasks, we conclude that they are heavily relying on face-to-face communication, and will be particularly hurt by social distancing. We use the model predictions to construct a combined index of disruption from social distancing.

A model of communication

Production involves sequentially completing tasks indexed by $z \in [0, 1]$. A single worker can do a range of tasks, but there is a benefit to specialization and division of labor [15,16]. The labor cost of a worker completing $Z < 1$ measure of tasks is $Z^{1+\gamma}/\gamma$, where $\gamma > 0$ captures the benefits to the division of labor. As we show below, the higher the γ, the more specialized each worker will be in a narrower set of tasks. Without loss of generality, we normalize the wage rate of workers to one so that all costs are expressed relative to worker wages.

Once the range of tasks Z is completed, the worker passes the unfinished product on to another worker. This has a cost of τ, which can capture the cost of communication (either face-to-face or online). The determinants of communication cost will be parametrized later. After all the tasks are completed, another step of communication with cost τ is needed to deliver the product to the customer. This captures the Marshallian externality that benefits firms that are close to their customers [14,17].

The firm will optimally decide how to share tasks between workers. The key trade-off is economizing on the cost of communication while exploiting the division of labor. Let n denote the number of workers involved in the production process. Because workers are symmetric, each works on $Z = 1/n$ range of tasks before passing the work to the next worker. Production involves $n - 1$ "contacts" (instances of communication) and there is an additional contact with the customer. Fig 1 illustrates the division of labor between the first three workers.

The firm's cost minimization problem can then be written as a function of the number of contacts alone,

$$c(\tau) = \min_n n\tau + \frac{1}{\gamma} n^{-\gamma}, \tag{1}$$

where total communication costs are $n\tau$ and production costs are $nZ^{1+\gamma}/\gamma$ with $Z = 1/n$.

Given the strict convexity of this cost function, and ignoring integer problems, the

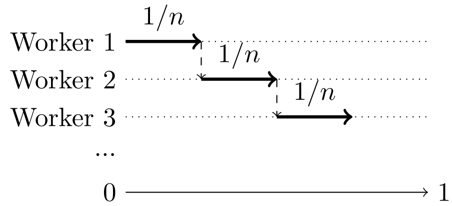

Fig 1. Workers take turns completing tasks. Horizontal movement represents production, vertical movement represents communication. Each worker works on a range $1/n$ of tasks, passing work $n-1$ times.

first-order condition is necessary and sufficient for the optimum,

$$n^*(\tau) = \tau^{-1/(1+\gamma)}. \tag{2}$$

The number of worker contacts is decreasing in the cost of communication, expressed relative to worker wage. When the division of labor is important, γ is high, and the number of contacts does not depend very strongly on communication costs.

The total cost of producing one good can be calculated by substituting in (2) into (1),

$$c(\tau) = \tau^{\chi}/\chi, \tag{3}$$

where $\chi = \gamma/(1+\gamma) \in (0,1)$ measures the importance of division of labor. This unit cost function is the same as if workers and communication were substitutable in the production function in a Cobb-Douglas fashion. Indeed, χ captures the share of costs associated with communication and can be calibrated accordingly.

The cost of communication

When workers meet face to face, communication costs depend inversely on the population density in the neighborhood of the firm, $\tau = d^{-\varepsilon}$ with $\varepsilon > 0$. This captures the other Marshallian externality of knowledge spillovers [17], which happen more easily in densely populated areas [18–20]. The number of contacts will be

$$n^*(d) = d^{\varepsilon(1-\chi)}. \tag{4}$$

Contacts will be more frequent in dense areas [20]. This follows directly from the cost function.

The unit cost of production is

$$c(d) = d^{-\varepsilon\chi}/\chi. \tag{5}$$

Firms in dense areas face lower unit costs [21], but this agglomeration benefit may be offset by higher wages and land rents in places with high population density [22–24]. In spatial equilibrium (not modeled here), firms with high communication needs will choose to locate in high-density areas.

Social distancing measures

We study the effect of a social distancing intervention that introduces an upper bound N on the number of face-to-face contacts. Firms can mitigate the disruption from this measure by moving communication online, but this is more costly per contact than face-to-face communication.

The optimal number of contacts without social distancing is given by Eq (4). Firms with $n^* > N$ are limited by social distancing. Without moving communication online, their unit cost will increase to $c' = Nd^{-\varepsilon} + N^{-\gamma}/\gamma$, which is greater than the optimal cost,

$$\frac{c'(d)}{c(d)} = \chi \frac{N}{n^*(d)} + (1-\chi)\left(\frac{N}{n^*(d)}\right)^{-\gamma} > 1. \tag{6}$$

The first term of the weighted average is less than one, representing a reduction in communication costs once the number of contacts is limited. The second term is greater than one due to the fact that every worker has to complete a wider range of tasks than before, and they lose the benefit of specialization. Because n^* is the cost-minimizing communication choice of the firm, the second term dominates, and production costs increase with social distancing.

If the firm chooses to use telecommunication, the cost per contact will be $T > d^{\varepsilon}$ (otherwise the firm would have used telecommunication before). The proportional increase in production costs in this case is given by

$$\frac{c''(d)}{c(d)} = T^{\chi} d^{\varepsilon\chi} > 1. \tag{7}$$

In both cases, the cost increase is highest for communication-intensive firms (large γ and χ) and those operating in a high-density area (high d and hence high n^*).

Fig 2 displays the ratio of production costs under social distancing to the optimal production costs as a function of density. Firms in low-density areas are unaffected by social distancing since they do not have many contacts anyway. Those in intermediate-density areas would suffer less of a cost increase by switching to telecommunication. Firms in the highest-density areas will stick to face-to-face communication, which is still the more efficient form of communication despite restrictions. However, they will suffer the greatest cost increase.

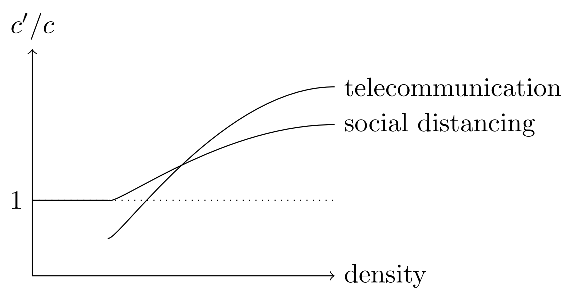

Fig 2. Both social distancing and telecommunication hurt firms in dense areas more. See Eq (6) and Eq (7) for the relative production costs under the two interventions.

Methodology

To estimate the potential disruptions from social distancing, we compute two measures. The first is the share of workers whose job requires personal communication. Communication-intensive sectors are for example "Retail stores," "Personal and laundry services," and "Education." Communication is not important in sectors like "Forestry and logging" and "Truck transportation." The idea behind this measure is that when workers in communication-intensive occupations stay at home, their productivity decreases. In our model, the parameter χ captures the share of costs spent on communication, which can be proxied by the share of workers in communication-intensive occupations within an industry.

The second measure captures how urbanized the industry is: what is the average population density in the ZIP-code of its establishments? This is high for sectors like "Performing arts" and "Securities and financial investments," and low for sectors like "Forestry and logging" and "Wood product manufacturing." Our second measure is motivated by the fact that communication-intensive sectors such as business services and advertising, together with central administrative offices of production firms tend to be concentrated in areas with high employment density [25]. Taken together, high values of both measures can indicate that face-to-face communication (as opposed to online communication or transportation) is used intensively in the sector.

We construct a combined index of exposure to social distancing as d^{χ}, where d is the average density of the industry and χ is the share of communication-intensive workers. This index is motivated by our model, where the proportional increase in production costs after social distancing depends on both density and communication, with this functional form.

We extend our analysis by calculating the share of workers within the sector who are highly exposed to infection either because they work in a disease-prone environment or because they work with many others in a confined space. This measure captures the primary motivation behind recent social distancing interventions. Workers at "Personal and laundry services" are highly exposed to infections, while infections are not relevant in sectors like "Crop production."

Although "Hospitals" are highly communication-intensive sectors and the workers are highly exposed to infection, this sector is removed from the analysis because of its inevitable role in combating the epidemic.

Data

We use Occupational Information Network (O*NET) [12] to measure the characteristics of a given occupation, similarly to previous studies [26, 27]. The O*NET dataset contains detailed standardized descriptions on almost 1,000 occupations along eight dimensions. We focus on the job characteristics that are related to the context of the work, while prior work focused mainly on activities that are required to perform a task [26, 27].

We compute two measures based on worker context in O*NET. The first one shows the importance of personal communication to perform the given job, which summarizes "contact with others," "deal with external customers," "face-to-face discussions" and "work with work group or team." Our second measure shows the exposure to infections. It is the average of "exposed to disease or infections" and "physical proximity." All indexes are between 0 and 100. We take a simple arithmetic average of the component indexes to compute the importance of communication and exposure to infections. We aggregate the measures to 6-digit occupation codes (Standard Occupational Classification; 2010-SOC). We have information on communication skill demand and infection exposure for 809 occupations in SOC 2010 codes.

The two measures are highly correlated (Fig 3), but they are conceptually different. While all medical occupations are communication-intensive and highly exposed to infections, "Fine Artists" are at the bottom of both of the distributions and "PR managers" is a communication-intensive occupation that is not exposed to infections.

As a next step, we calculate the share of workers whose job requires a high-level of personal communication and share of workers who are highly exposed to infection by sectors. We use the same sectoral breakdown as the Current Employment Statistics (CES) [28]. A job is defined to be communication-intensive if it is in the top 25 percent of the skill distribution, we define a job to be highly exposed to infection in the same way. The occupation structure of the industries are retrieved from the official

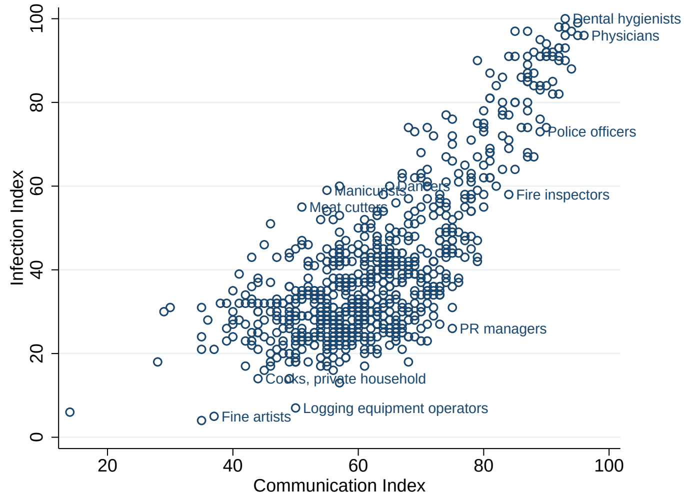

Fig 3. Communicating with others and exposure to infections are highly correlated. Each circle represents an occupation. Communication and infection indexes are constructed as explained in main text.

industry-occupation matrix [29], we use the employment statistics by occupation-industry for 2018.

The location of sectors comes from the County Business Patterns (CBP) data for 2017 [13]. For a finer spatial resolution, we use the data tabulated by ZIP-Code Tabulation Areas. The CBP lists the number of establishments of a certain size for each ZIP-code and NAICS industry code. Because establishment sizes are given in bins (e.g., 1–4 employees), we take the midpoint of each bin as our estimated employment (e.g., 2.5 employees). In small industries and ZIP codes, the Census omits some size categories to protect the confidentiality of businesses. We impute employment in these plants from the national size distribution of plants in the same NAICS industry. Our estimated industry-level employment is a very good approximation to official employment statistics. The correlation between our estimates based on CBP and the employment reported in CES is 0.96.

We compute the average population density for each sector as the employment-weighted population density across ZIP codes in which the sector is located. Urban sectors will employ most of their workers in high-density areas, hence, their average density will be high. We also experimented with using employment densities instead of population densities. Results were very similar, as the two measures are highly correlated with the exception of very high employment-density urban centers where population is more sparse [30].

Results

Table 1 displays the top five and the bottom five industries (excluding hospitals and clinics) as sorted by the combined disruption from social distancing. The most affected sectors have both high communication intensity and tend to be located in dense cities. Since the County Business Patterns data does not include farm businesses, some sectors (e.g., “Postal Service,” “Crop production”) are missing an estimated population density. But these sectors tend to be more rural and would suffer low disruptions anyway.

Fig 4 plots our three index measures across ZIP codes by population density. Both communication and infection intensity are higher in dense areas [20]. In the highest

Table 1. Communication-intensive urban industries are most disrupted by social distancing.

Industry	Comm.	Infection	Density	Soc.dist.
Transit & ground passenger	42	59	3466	173
Motion picture recording	27	18	5730	163
Personal and laundry services	41	60	2407	147
Food and beverage stores	44	7	2081	142
Education services	25	36	3580	140
...				
Wood product manufacturing	1	3	464	99
Fishing, hunting and trapping	5	8	655	98
Beverage and tobacco product	6	3	584	97
Air transportation	29	48	818	96
Support for agri. & forestry	3	5	201	95

"Comm." and "Infection" show the percentage of workers in communication-intensive and infection-prone occupations, respectively. "Density" shows the average population density in the same ZIP code as the industry establishments. "Soc.dist." shows the combined social distancing index (with the median manufacturing sector normalized to 100), with higher values corresponding to larger exposure.

population density ZIP-codes, 23 percent of workers are employed in communication-intensive occupations. The combined index of social distancing exposure increases even more sharply with density. This is because dense areas are both assumed to have lower communication costs and a larger fraction of people engaging in communication. Hence the densest locations are hurt the most by social distancing.

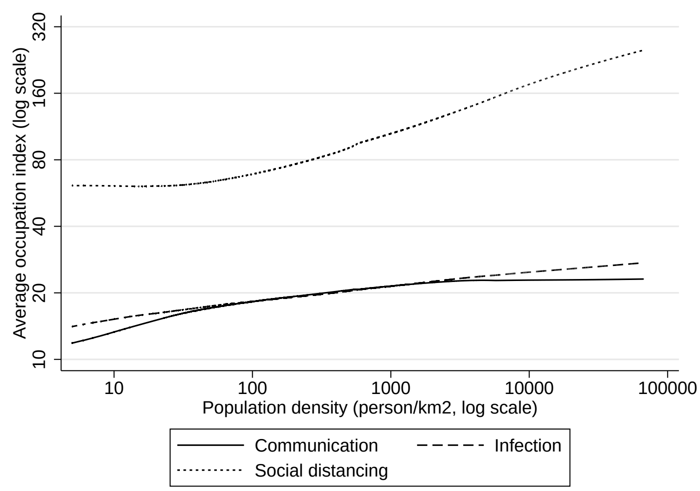

Fig 4. Urban areas employ more communication-intensive and infection-prone workers. Locally weighted polynomial regression of average communication intensity, infection exposure, and social distancing exposure across sectors within the ZIP code (bandwidth= 0.5).

Excluding hospitals and clinics, the ten industries most disrupted by social distancing altogether employ 22.9 million workers in the U.S.

Discussion and conclusions

Our model of division of labor is motivated by [15] and uses a similar functional form as [16]. We model face-to-face and telecommunications as perfect substitutes. The only distinction is that the efficiency of face-to-face meetings improves with population density, whereas telecommunication does not depend on agglomeration [18, 19]. Previous work has found face-to-face communication to be more effective in high-intensity communication which is particularly helpful to overcome incentive problems in joint production [31, 32]. Data on internet flows suggests that telecommunication is not a good substitute for face-to-face meetings [33], which we can approximate in our framework with a large T.

Our prediction that there is more business communication within large cities is borne out by worker-level survey evidence from France [20], which motivates our empirical measures. In spatial equilibrium (not modeled here), when other firms are also changing their communication patterns within the city, the communication externality will also decrease with social distancing measures. This can affect our conclusion about who uses telecommunication.

We have modeled the production disruptions from social distancing, but our framework remained silent about the demand side. This leaves open two avenues for future research. First, consumption may also be disrupted by social distancing. For example, restaurants, sports and music events, airplane trips all require physical proximity of consumers and will suffer a drop in demand during epidemics. We expect that our theoretical framework can be adapted to model consumption limitations, but new empirical measures may be needed.

Second, the employment response to a production disruption greatly depends on the elasticity of demand. We hypothesize that sectors like schooling and health care have inelastic demand and will continue to employ many workers despite significant disruptions. However, personal services, small grocery stores and restaurants may face more elastic demand and respond to large production cost increases by laying off a significant fraction of their work force.

Studying interaction between sectors and regions can also be interesting, as this can strongly affect the propagation of shocks and aggregate consequences [34, 35].

Supporting information

S1 Full table of sectors. Social distancing exposure by sector. Available at https://github.com/ceumicrodata/social-distancing/blob/master/data/derived/industry-index.csv.

S2 Full table of ZIP-codes. Social distancing exposure by location. Available at https://github.com/ceumicrodata/social-distancing/blob/master/data/derived/location-index.csv.

S1 Data repository. Replication code and data. Replication code and data are available at https://github.com/ceumicrodata/social-distancing.

Acknowledgments

References

1. Bootsma MCJ, Ferguson NM. The effect of public health measures on the 1918 influenza pandemic in US cities. Proc Natl Acad Sci. 2007;.
2. Markel H, Lipman HB, Navarro JA, Sloan A, Michalsen JR, Stern AM, et al. Nonpharmaceutical interventions implemented by US cities during the 1918-1919 influenza pandemic. JAMA. 2007;298(6):644–654.
3. Hatchett RJ, Mecher CE, Lipsitch M. Public health interventions and epidemic intensity during the 1918 influenza pandemic. Proc Natl Acad Sci. 2007;104(18):7582–7587.
4. Wilder-Smith A, Freedman DO. Isolation, quarantine, social distancing and community containment: pivotal role for old-style public health measures in the novel coronavirus (2019-nCoV) outbreak. J Travel Med. 2020;27(2).
5. Anderson RM, Heesterbeek H, Klinkenberg D, Hollingsworth TD. How will country-based mitigation measures influence the course of the COVID-19 epidemic? Lancet. 2020;.
6. Cohen J, Kupferschmidt K. Mass testing, school closings, lockdowns: Countries pick tactics in 'war' against coronavirus. Science. 2020;.
7. Adda J. Economic Activity and the Spread of Viral Diseases: Evidence from High Frequency Data. Q J Econ. 2016;131(2):891–941.
8. Henderson JV. Cities and Development. J Reg Sci. 2010;50(1):515–540.
9. Henderson V. Urbanization in Developing Countries. World Bank Res Obs. 2002;17(1):89–112.
10. Herrendorf B, Rogerson R, Valentinyi Á. Growth and Structural Transformation. In: Aghion P, Durlauf SN, editors. Handbook of Economic Growth. vol. 2. Elsevier; 2014. p. 855–941.
11. Duarte M, Restuccia D. Relative Prices and Sectoral Productivity. J Eur Econ Assoc. 2019;.
12. National Center for O*NET Development. O*NET OnLine; 2020.
13. U S Bureau of the Census. County Business Patterns; 2017.
14. Krugman P. Geography and Trade. Cambridge: MIT Press; 1991.
15. Smith A. An Inquiry into the Nature and Causes of the Wealth of Nations (Book I). London: W. Strahan; T. Cadell; 1778.
16. Fally T, Hillberry R. A Coasian model of international production chains. J Int Econ. 2018;114:299–315.
17. Marshall A. Principles of Economics (eighth edition). London: MacMillan; 1920.
18. Rossi-Hansberg E, Wright MLJ. Urban Structure and Growth. Rev Econ Stud. 2007;74(2):597–624.

19. Ioannides YM, Overman HG, Rossi-Hansberg E, Schmidheiny K, Moav O. The Effect of Information and Communication Technologies on Urban Structure. Econ Policy. 2008;23(54):201–242.

20. Charlot S, Duranton G. Communication externalities in cities. J Urban Econ. 2004;56(3):581–613.

21. Ciccone A, Hall R. Productivity and the Density of Economic Activity. Am Econ Rev. 1996;86(1):54–70.

22. Eberts RW, Gronberg TJ. Wage gradients, rent gradients, and the price elasticity of demand for housing: An empirical investigation. J Urban Econ. 1982;12(2):168–176.

23. Madden JF. Urban wage gradients: Empirical evidence. J Urban Econ. 1985;18(3):291–301.

24. Combes PP, Duranton G, Gobillon L. The Costs of Agglomeration: House and Land Prices in French Cities. Rev Econ Stud. 2019;86(4):1556–1589.

25. Aarland K, Davis JC, Henderson JV, Ono Y. Spatial organization of firms: the decision to split production and administration. Rand J Econ. 2007;38(2):480–494.

26. Firpo S, Fortin NM, Lemieux T. Occupational Tasks and Changes in the Wage Structure. IZA; 2011. 5542.

27. Autor DH, Dorn D. The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. Am Econ Rev. 2013;103(5):1553–1597.

28. U S Bureau of Labor Statistics. Current Employment Statistics; 2020.

29. U S Bureau of Labor Statistics. National Employment Matrix; 2020.

30. Heblich S, Redding SJ, Sturm DM. The Making of the Modern Metropolis: Evidence from London; 2017.

31. Gaspar J, Glaeser E. Information Technology and the Future of Cities. J Urban Econ. 1998;43(1):136–156.

32. Storper M, Venables AJ. Buzz: face-to-face contact and the urban economy. J Econ Geogr. 2004;4(4):351–370.

33. Cuberes D. Are Internet and Face-to-Face Contacts Complements or Substitutes? Evidence from Internet Traffic between Cities; 2013. 2013010.

34. Caliendo L, Parro F, Rossi-Hansberg E, Sarte PD. The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy. National Bureau of Economic Research, Inc; 2014. 20168.

35. Caselli F, Koren M, Lisicky M, Tenreyro S. Diversification Through Trade. Q J Econ. 2020;135(1):449–502.