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Social learning along international migrant networks☆

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ABSTRACT

We document the transmission of social distancing practices from the United States to Mexico along migrant networks during the early 2020 Covid-19 pandemic. Using data on pre-existing migrant connections between Mexican and U.S. locations and mobile-phone tracking data revealing social distancing behavior, we find larger declines in mobility in Mexican regions whose emigrants live in U.S. locations with stronger social distancing practices. We document the absence of confounding pre-trends and use a variety of controls to rule out the potential influence of disease transmission, migrant sorting between similar locations, and remittances. Given this evidence, we conclude that our findings represent the effect of information transmission between Mexican migrants living in the U.S. and residents of their home locations in Mexico. Our results demonstrate the importance of personal connections when policymakers seek to change fundamental social behaviors.

1. Introduction

Social networks are a critical source of new information. By interacting with family, friends, and acquaintances, individuals learn new facts, observe the implications of others' decisions, and encounter new social norms. This type of social learning can be valuable when facing uncertainty about the nature of the choices one faces or the efficacy of one choice in comparison to others. Such uncertainty is particularly acute when one faces a novel set of choices and when the stakes are high. For example, in a time of pandemic when people must quickly learn about the nature of a novel disease and the appropriate actions to take in response, social learning can play an especially important role.

We document the transmission of social distancing practices from the United States to Mexico along migrant networks during the early 2020 Covid-19 pandemic. Social distancing is considered effective in reducing the spread of the novel coronavirus that causes Covid-19 and has been encouraged by public health organizations and most national and local govern-

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ments.[1] The outbreak of Covid-19 in the United States emerged about two weeks earlier than in Mexico, and in the United States there was substantial spatial variation in timing of and compliance with social distancing policies. Using data on pre-existing migrant connections between Mexican and U.S. locations and mobile-phone tracking data revealing social distancing behavior, we find larger declines in mobility in Mexican regions whose emigrants live in U.S. locations with stronger social distancing practices. After ruling out confounding pre-trends and the potential influence of disease transmission, migrant sorting between similar locations (e.g., urban vs. rural areas), and remittances, we conclude that our findings represent the effect of information transmission between Mexican migrants living in the U.S. and residents of their home locations in Mexico.

Key to our analysis is the ability to observe pre-existing migrant connections between Mexican source regions (*municipios*) and U.S. counties. We do so using administrative data from the *Matrícula Consular de Alta Seguridad* (MCAS) program, which provides identity cards to Mexicans living in the U.S. Prior work has confirmed the quality and representativeness of these data, which allow us to measure the extent to which each Mexican *municipio* was exposed to each U.S. county through the migrant network.[2] We combine these data with observed social distancing measures derived from smartphone geolocation data collected by Facebook and Unacast for the U.S. and Facebook for Mexico.[3] The Facebook data report the reduction in the number of 0.6 km-square tiles visited each day, while Unacast reports the reduction in daily distance traveled. These data sources allow us to observe the behavior of interest (social distancing) and to do so with high frequency and fine geographic granularity. For each *municipio*, we calculate the migration-network-weighted average of social distancing across U.S. counties. Because social distancing varied substantially across U.S. counties, and migrants from different *municipios* go to very different sets of U.S. destinations, there is significant variation in exposure to U.S. social distancing across *municipios*.

Our empirical analysis examines how observed reductions in movement among people living in Mexico relate to this variation in migrants' exposure to U.S. social distancing. We find that *municipios* with a one-standard-deviation larger exposure to U.S. social distancing had a 0.51 standard-deviation larger decline in mobility. This finding is not driven by pre-existing trends and is robust to controlling flexibly for the number of local Covid-19 cases; the number of cases in migrant-connected U.S. counties; and baseline local characteristics including population density, urban status, age distribution, education, income, the employment rate, and remittances. The effect estimate also remains effectively unchanged when controlling for U.S. and Mexican government stay-at-home orders. When investigating heterogeneity in this effect, we find it is stronger in *municipios* with initially higher population density, higher urbanization rate, higher education levels, higher income level, higher employment rates and lower initial exposure to remittances. In terms of the characteristics of migrant-connected U.S. counties, we find some evidence that *municipios* connected to U.S. counties with higher share of Hispanic and Mexican population responded more strongly to the exposure to U.S. social distancing.

How should one interpret these results? There are several mechanisms that might generate an observed relationship between social distancing behavior in a Mexican *municipio* and in migrant-connected U.S. counties. First, migrants in the U.S. may observe the importance of social distancing during the U.S. outbreak, and may communicate that information back to people in their home region in Mexico, leading to more social distancing there as well. We refer to this as the "information" channel. Second, return migrants or others may have moved between the U.S. and Mexico, transmitting the disease and leading to correlated outbreaks in the two locations, which may in turn lead to correlated social distancing. We refer to this as the "disease transmission" channel. Third, migrants from locations with a higher likelihood of Covid-19 outbreak or with a higher likelihood of compliance with public health orders may choose similar locations in the U.S. If this is the case, then observed correlations between migrant-connected locations simply result from migrants' selection of destinations rather than reflecting a causal effect. We refer to this as the "migrant sorting" channel. Finally, migrants living in harder-hit U.S. locations may have reduced remittance transfers to family members in Mexico, potentially leading to less economic activity and changing mobility in source regions in Mexico. We refer to this as the "remittance" channel.

Our empirical findings strongly reject the disease transmission, migrant sorting, and remittance channels. The observed relationship between U.S. and Mexican social distancing is barely affected when controlling flexibly for the number of cases in either location, implying that disease transmission is not driving our results. We address the possibility of migrant sorting first by controlling for pre-pandemic characteristics in the relevant *municipio*, including population density, urban status, age distribution, education, income, and the employment rate. As discussed below, these features are relevant for disease transmission and compliance with social distancing, but controlling flexibly for them has minimal effect on our results. We also control for government stay-at-home orders in both countries, which captures potential migrant sorting into places with similar public health responses, again finding nearly identical results. Finally, we rule out the remittance channel by controlling for initial remittances per capita and the share of household receiving any remittance payments in source locations,

[1] Examples include the World Health Organization (WHO, 2020), the U.S. Centers for Disease Control and Prevention (CDC, 2020), and the Mexican Health Ministry (Secretaría de Salud, 2020).

[2] Caballero et al. (2018) confirm the quality and representativeness of the MCAS data by comparing it against gold-standard household survey data. Other papers using data derived from the same underlying source include Albert and Monras (2019), Allen et al. (2019) and Caballero et al. (2020). These papers and Caballero et al. (2018) each use slightly different extracts from the same underlying data source. As in Caballero (2020), we use the most detailed geographic information available (*municipio* by county) and use a version of the 2019 data that was cleaned and matched to valid *municipio* and county names by the *Instituto de los Mexicanos en el Exterior*.

[3] Similar data have been used to study migration (Blumenstock et al., 2019), segregation (Athey et al., 2019), commuting (Kreindler and Miyauchi, 2019), friendship (Kreindler and Miyauchi, 2019), and the spreading of disease (Kuchler et al., 2021), and are used in many of the papers cited below that focus on social distancing in response to Covid-19.

with minimal impact on the relationship between U.S. and Mexican social distancing. Together, these findings reject the disease transmission, migrant sorting, and remittance channels, leaving the information channel as the most likely explanation for the observed relationship between U.S. and Mexican social distancing.

Our analysis relates to the large literature examining how social network connections reduce information frictions and facilitate learning. Papers in this literature cover a wide range of topics including technology adoption, labor markets, international trade, and many others.[4] A minority of these papers implements randomized controlled field trials, which include baseline network measures, randomized information interventions, and follow-up surveys measuring information transmission.[5] In contrast, much of this literature infers the presence of social learning based on equilibrium outcomes in the absence of a well-defined information shock.[6] We contribute a clear example of social learning in an observational setting where we have a well-defined and credibly exogenous information shock, a high-quality measure of spatial network connections, and observed changes in behavior that are closely linked to the new information.

As in our setting, a number of papers in this broader literature focus on situations where immigrants transmit information across international borders. Examples include studies finding that immigrants increase trade with their source countries (Gould, 1994; Head and Ries, 1998; Rauch and Trinidade, 2002), transfer knowledge through co-ethnic patent citations (Kerr, 2008), influence source country political preferences (Barsbai et al., 2017; Karadja and Prawitz, 2019) or fertility norms (Beine et al., 2013), and facilitate FDI and venture capital funding relationships with the source country (Dimmock et al., 2019; Kugler and Rapoport, 2005; Li, 2020; Pandya and Leblang, 2017). We introduce a new example of cross-country information transmission through migrant networks, documenting migrants' role in spreading public-health information with potential life-and-death consequences. Moreover, we show that these responses can arise very quickly, with migrant source regions benefiting from destination-country information nearly in real time.

Our paper also contributes to the emerging literature examining the determinants of compliance with public health recommendations in the midst of Covid-19 outbreaks. Contemporaneous work shows that social distancing compliance varies with civic capital (Barrios et al., 2021), trust in science (Brzezinski et al., 2020), education and income (Brzezinski et al., 2020; Wright et al., 2020), partisanship (Allcott et al., 2020; Fan et al., 2020), media consumption (Ananyev et al., 2021; Simonov et al., 2020), political leaders' speech (Ajzenman et al., 2020), and whether workers can telework (Mongey et al., 2021). Additional work finds that many of these factors can impact the realized number of Covid-19 cases and resulting deaths (Bursztyn et al., 2020; Desmet and Wacziarg, 2021). Our work shows how migrants' experiences with U.S. Covid-19 outbreaks affect the social distancing behavior of those remaining in Mexico. This cross-country context is (to our knowledge) novel in this literature, and it helps avoid a number of potential pitfalls present in single-country designs.

For example, in a closely related paper Holtz et al. (2020) examine spillover effects of social distancing policies across U.S. counties, based on pre-existing mobility patterns and social-network friendship connections. Although we address similar questions, Holtz et al. (2020) face a much more challenging causal identification problem, because they examine spillovers between U.S. counties. It is quite likely that a U.S. county's choice of social-distancing policy is affected by those of neighboring counties, both for public health and political reasons, so reverse causality is a substantial concern, which the authors address using an instrumental variables strategy.[7] In our context, it is far less likely that U.S. social distancing practices or policies were influenced by Mexican practices or policies, mitigating concerns about reverse causality. The primary remaining threat to causal inference is the possibility of migrant sorting. As discussed above, we are able to allay these concerns using flexible controls for regional characteristics that may be relevant for sorting. Thus, our setting provides a relatively clean test of the importance of social connections in driving compliance with public health recommendations during the pandemic.

The rest of the paper is organized as follows. Section 2 presents the institutional background on the Covid-19 epidemic and the U.S.-Mexico ties. Section 3 discusses the data on mobility and migrant networks. Section 4 shows the main empirical results on the effect of exposure to U.S. social distancing, and Section 5 investigates heterogeneous effects by origin and destination characteristics. The last section concludes.

2. Institutional background

2.1. The Covid-19 pandemic

Covid-19 is a respiratory disease caused by a novel coronavirus (SARS-CoV-2). After the first case was reported in Wuhan, China on December 31, 2019, it spread across the world rapidly, despite containment efforts by various governments and

[4] BenYishay and Mobarak (2019) and Miller and Mobarak (2015) study information transmission in agricultural technology adoption; Barwick et al. (2019), Beaman (2012), Dustmann et al. (2016), Edin et al. (2003), and Munshi (2003) study the role of social networks and immigrant enclaves in job referrals and labor market outcomes; Büchel et al. (2020) examine how networks affect spatial mobility; Burchardi and Hassan (2013) show how social ties affect entrepreneurial activity and firm investment.

[5] Prominent examples include Beaman et al. (2021), Banerjee et al. (2019), BenYishay and Mobarak (2019). See Breza et al. (2019) for a survey of the literature on networks in economic development.

[6] Conley and Udry (2010) provide a plausibly exogenous and well-defined shock in an observational setting, studying social learning patterns in the adoption of fertilizer use. The authors use survey data to measure farmers' information networks and find that they change their fertilizer use in response to unexpectedly high or low profits received by their information neighbors, while controlling for a wide array of potential confounders.

[7] Holtz et al. (2020) address this potential reverse causality issue using weather and industry shift-share instruments.

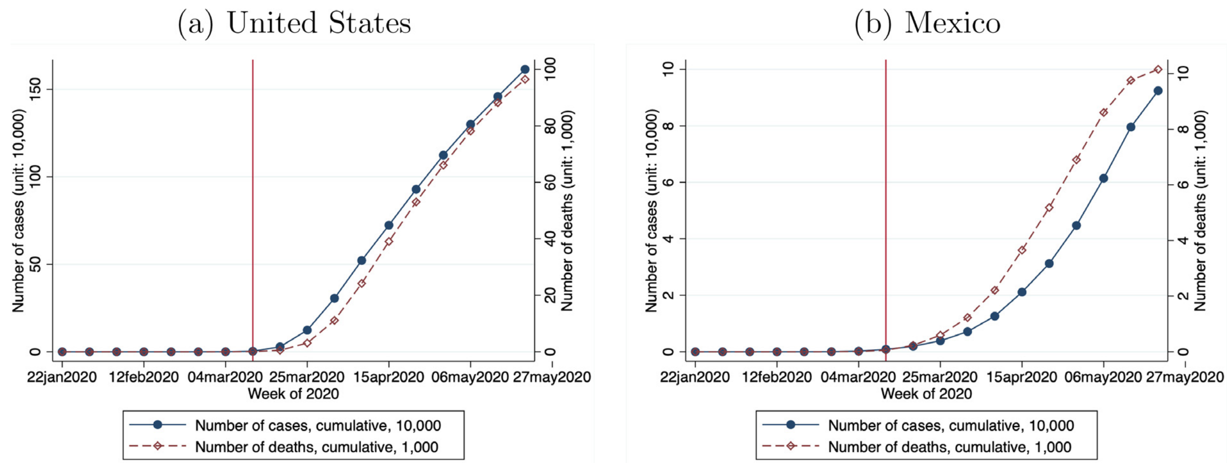

Fig. 1. The U.S. outbreak began earlier and was more severe than that of Mexico by Week 21. *Note:* The number of cases and deaths in the United States are from Johns Hopkins University: https://coronavirus.jhu.edu/. The corresponding information in Mexico is from the Mexican Ministry of Health: https://coronavirus.gob.mx/. The horizontal axis represents the week of the year in 2020. For example, Week 4 is from Jan 22 to Jan 28, and Week 21 is from May 20 to May 26. The vertical line at Week 11 denotes the week when a national emergency was declared in the United States (March 13). See the details of the correspondence between dates and weeks of 2020 in Appendix Table A1.

organizations.[8] The World Health Organization (WHO) characterized Covid-19 as a pandemic on March 11, 2020, and by June 12, 2020, there were 7,533,182 cases, 423,349 confirmed deaths, and 216 countries, areas, or territories with cases worldwide.[9]

The epicenter of the outbreak has been shifting over time. After China's initial outbreak and lockdown measures in January and February, the epicenter shifted to Europe in mid March, followed by the United States starting from late March, and by June, further shifted to Latin American countries. In the United States, the first case was reported on January 22, 2020, and President Trump declared a national emergency on March 13, (in the 11th week of 2020, shown in Fig. 1 with a red vertical line).[10] As of June 12, 2020, the total number of U.S. cases was 2,016,027 and the number of deaths was 113,914.[11] Figure 1 Panel (a) shows the number of cases (solid circles) and number of deaths (hollow diamonds) from Week 4 of 2020 (Jan 22–28) to Week 21 (May 20–26). The numbers of U.S. cases and deaths began increasing rapidly after Week 13. The outbreak in Mexico emerged slightly later. The first case was confirmed on February 28, 2020, and the increase in the number of cases and number of deaths accelerated after Week 15 (Fig. 1 Panel b). By the end of Week 22, there were 47.7 cases and 2.9 deaths per 10,000 U.S. population, and there were 8.2 cases and 0.9 deaths per 10,000 Mexican population.[12]

The Covid-19 outbreak was unexpected, and in many ways unprecedented, meaning that governments and public health organizations had much to learn regarding how to appropriately respond.[13] As an example, Italy declared a state of emergency on Jan 31, 2020 and subsequently halted air traffic to and from China.[14] However, the disease continued to spread, and a national lockdown was imposed on March 9, 2020, when Italy became the epicenter of the pandemic. Strict travel restrictions were in place, only essential businesses were allowed to open, and people were required to maintain at least one meter of distance from one another in public spaces.[15] In the case of the U.S., although international travel restrictions with China were in place relatively early, the effectiveness of this and other policies has been debated. After one week of the

[8] See the detailed WHO timeline at https://www.who.int/news/item/27-04-2020-who-timeline-covid-19.

[9] The following declaration was accessed on June 13, 2020: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-happen.

[10] Declaration of a national emergency: https://trumpwhitehouse.archives.gov/presidential-actions/proclamation-declaring-national-emergency-concerning-novel-coronavirus-disease-covid-19-outbreak/.

[11] The following source was accessed on June 13, 2020: https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html.

[12] Note that observed cases and deaths are subject to testing capacity and reporting errors. In the case of Mexico, for example, there are concerns about the hidden death toll: https://www.nytimes.com/2020/05/08/world/americas/mexico-coronavirus-count.html.

[13] In WHO's announcement of the pandemic, the WHO Director-General said that "we have never before seen a pandemic sparked by a coronavirus. This is the first pandemic caused by a coronavirus. And we have never before seen a pandemic that can be controlled, at the same time." (https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19-11-march-2020).

[14] https://www.reuters.com/article/china-health-italy/italy-govt-agrees-state-of-emergency-after-confirmed-coronavirus-cases-govt-source-idUSR1N282044

[15] https://www.nytimes.com/2020/03/09/world/europe/italy-lockdown-coronavirus.html

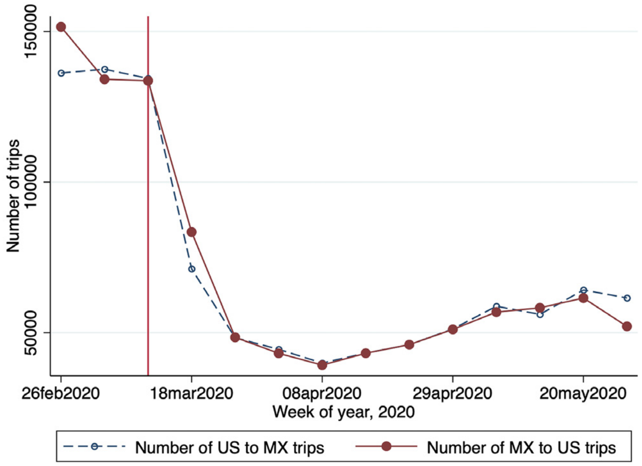

Fig. 2. Number of trips between the U.S. and Mexico declined after Week 11 (March 13–17). *Note:* The trip counts are calculated using Facebook mobile app users who opt into location services. The horizontal axis is the week of the year 2020, and the vertical axis is the average number of trips per day during the week. Week 9 is from Feb 26 to March 3, and Week 21 is from May 20 to May 26. The vertical line at Week 11 denotes the week when the national emergency was declared in the United States.

outbreak in the State of Washington, the White House issued social-distancing guidelines on March 16; recommendations regarding the use of cloth face coverings were issued by the Centers for Disease Control and Prevention (CDC) on April 3.[16]

Individuals also report learning from the experiences of others in their social networks. In Prato, Italy, where a quarter of the population is ethnic Chinese, residents voluntarily quarantined and practiced social distancing much earlier than those in the rest of the country, after learning about the success of similar measures in China, leading to very low rates of infection and transmission.[17] Similarly, restaurants owned by Chinese immigrants in the U.S. began scaling up takeout and delivery operations prior to the U.S. outbreak, based on information from similar businesses in China.[18] In a within-country context, Holtz et al. (2020) find that social distancing in U.S. regions significantly influenced policies and behaviors in other parts of the country.

2.2. Mexico-U.S. migration

The U.S. and Mexico have long been closely linked in terms of trade and migration. The U.S. is Mexico's most important trading partner, accounting for 76% of Mexican exports in 2018, and 96% of those who reported living abroad five years prior to the 2010 Mexican Census.[19] Mexican migrants in the U.S. maintain close ties with their friends and family in Mexico. According to data from the Mexican Migration Project (MMP), an average Mexican migrant sends 27% of income earned in the U.S. back to Mexico, a much higher share than saving (20%), food budget (19%), or rent (18%).[20] During their first trip to the U.S., 61% of migrants received financial help from people in their home community. Such close ties do not deteriorate much along repeated migration trips; even in their last trip to the U.S., 51% received financial help. It is therefore entirely plausible that information regarding pandemic response would be transmitted from U.S. migrants to contacts in their home communities.

During a pandemic, the intensive flow of goods and people between the U.S. and Mexico can transmit both disease and information.[21] However, due to the travel restrictions imposed early in the pandemic, the number of trips across the U.S.-Mexico border fell substantially, as shown in Fig. 2, which reports the number of trips between the two countries as recorded among Facebook mobile app users. Initially there were more than 134,000 trips per day from Mexico to the U.S., and more than 137,000 trips from the U.S. to Mexico, but the numbers declined sharply after Week 11 when the U.S. declared a national emergency and imposed more strict travel restrictions. By Week 15, the number of trips declined to 40,000 per

[16] The details and timeline of the Washington outbreak: https://www.kiro7.com/news/local/coronavirus-washington-state-timeline-outbreak/IM65JK66N5BYTIAPZ3FUZSKMUE/. Social distancing guidelines: https://trumpwhitehouse.archives.gov/articles/president-trump-actions-to-confront-pandemic/. Face covering recommendations: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/diy-cloth-face-coverings.html.

[17] https://www.reuters.com/article/us-health-coronavirus-italy-chinese/from-zero-to-hero-italys-chinese-help-beat-coronavirus-idUSKBN21I3I8

[18] https://www.npr.org/2020/05/13/855791740/episode-999-the-restaurant-from-the-future

[19] *Sources:* trade data: https://wits.worldbank.org/countrysnapshot/en/MEX ; 2010 Mexican Census: IPUMS International (Minnesota Population Center, 2020).

[20] The Mexican Migration Project is a collaborative research project based at Princeton University and the University of Guadalajara. The data are publicly available at: https://mmp.opr.princeton.edu/. The figures here were calculated using a sample of 8823 individuals who had a previous trip to the U.S., using survey years from 1982 to 2018.

[21] For example, Kuchler et al. (2021) use Facebook friendship data between U.S. counties to show that the outbreak followed these connections.

Table 1
Summary of statistics for Mexico-U.S. migration networks using the 2019 MCAS data.

Variable	Value
Number of Mexican *municipios*	2,409
Number of U.S. counties	2,571
Number of county-*municipio* pairs (links)	166,939
Mean (s.d.) number of migrants per link	4.8 (24)
Min (max) number of migrants per link	1 (3,607)

Note: 2019 MCAS data. A link is a municipio-county pair, and the number of migrants per link is the number of Mexicans from the origin municipio who reside in the corresponding destination county in the U.S.

day on both sides, with a slight increase afterwards. Although cross-border flows have fallen by about two-thirds since early March, many people still cross the border each day. Our empirical analysis will therefore address the possibility of physical disease transmission along with potential information flows through migrant networks.

3. Data and measurement

3.1. Migrant network between Mexico and the U.S.

We use administrative information from the *Matrícula Consular de Alta Seguridad* (MCAS) program to measure migration networks between the U.S. and Mexico at the sub-national level. The MCAS card, which acts as an official form of identification for banking purposes and other transactions, is issued by Mexican consulates to Mexican citizens living in the U.S.[22] The MCAS administrative dataset contains annual counts of newly issued MCAS cards by place of birth in Mexico and place of residence in the U.S. These data likely pertain to unauthorized Mexican-born migrants, who have the strongest incentive to obtain a *matrícula* in the absence of access to other officially recognized forms of identification in the U.S (Massey et al., 2010). However, Caballero et al. (2018) show that MCAS migration network measures strongly agree with the source and destination distributions of *all* Mexican-born migrants irrespective of legal status. Our analysis should therefore reflect the average effects of information transmission from both authorized and unauthorized migrants in the U.S.

We construct the migration network measure as the share of *matrículas* issued in 2019 to Mexican-born migrants from each Mexican *municipio* living in each U.S. county. Summary statistics appear in Table 1. There are 166,939 *municipio*-county pairs, with 2,409 origin *municipios* and 2,571 destination U.S. counties in the 2019 MCAS dataset. The average number of migrants per link is 4.8, but it varies substantially, ranging from 1 to 3607.

Our empirical analysis relies on the fact that migrants from different *municipios* choose quite different destinations in the U.S. and therefore are exposed to different social distancing practices in different parts of the country. Figure 3 shows the destination distribution for two different *municipios* in the state of Michoacán: Huandacareo and Puruándiro. Despite these two sources being located very close to each other (less than an hour apart by car) and thus roughly equal distances from particular U.S. labor markets, there are large differences in the U.S. destinations selected by migrants from these two *municipios*. Chicago (Cook County) is by far the most common destination for migrants from Huandacareo, while the most common destination for migrants from Puruándiro is Tulare county in California's Central valley. Because social distancing behavior differed across these U.S. destinations (shown in Fig. 4 below), migrants from Huandacareo and Puruándiro will be exposed to different degrees of social distancing in the U.S. This example is representative in the sense that migrants from otherwise similar *municipios* often exhibit quite different destination distributions in the U.S. (Caballero et al., 2018), leading to variation in exposure to U.S. social distancing across *municipios*.

3.2. Unacast and Facebook data on local mobility

We use two data sources to measure changes in mobility. Due to the nature of Covid-19 transmission, scientists have identified social distancing as one of the key measures to combat the pandemic (Hsiang et al., 2020 and Anderson et al., 2020).[23] The ideal measure of social distancing would capture whether people are in close proximity to one another, particularly when in poorly ventilated indoor spaces, since this is the circumstance under which Covid-19 transmission is most likely. Although available data do not capture this ideal social distancing measure, we are able to observe changes in general geographic mobility. While not directly measuring proximity to other individuals, these mobility measures will capture social distancing behaviors associated with avoiding public places, self-quarantining, working from home, etc.

Our first mobility measure is from Unacast, a New York based technology company (Unacast, 2020). The dataset uses location information from 15 to 17 million smartphones to calculate the average distance travelled each day. We measure the county-level mobility reduction as the percentage reduction in the average distance traveled compared to the same day

[22] See Caballero et al. (2018) for more detail on the MCAS program and data.

[23] See CDC recommendation at: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html.

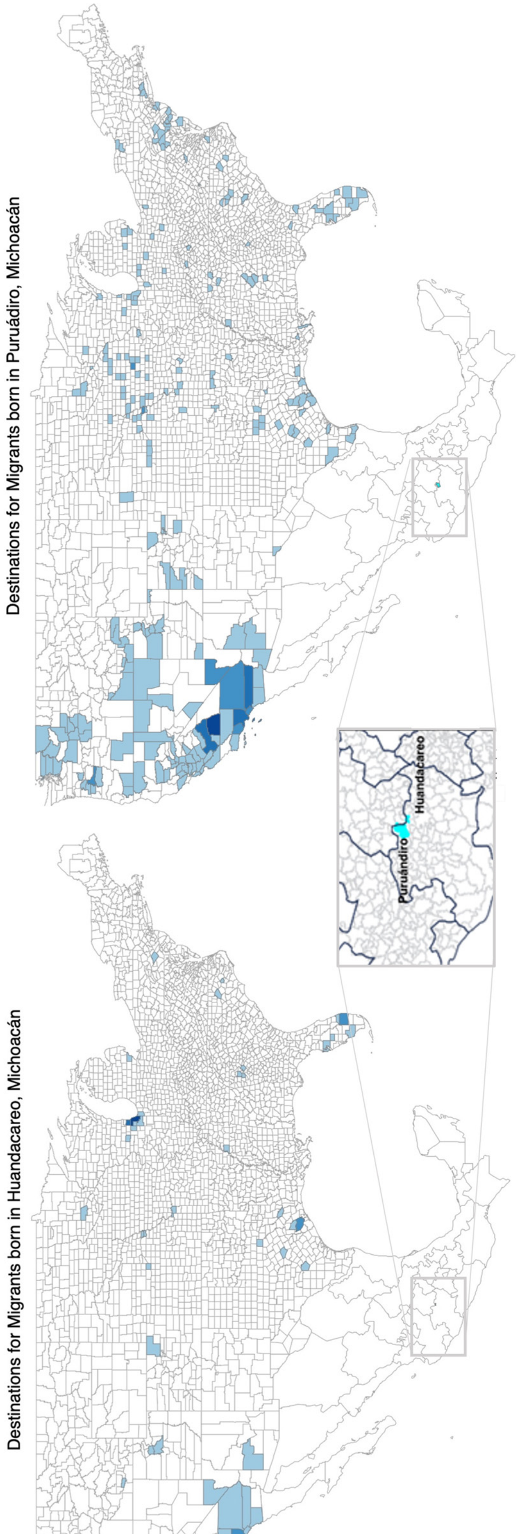

Fig. 3. Differences in migrant destination distributions. *Note:* 2019 MCAS data. The left panel shows the distribution across U.S. counties for migrants from Huandacareeo, and the right panel shows the same for migrants from Puruándiro.

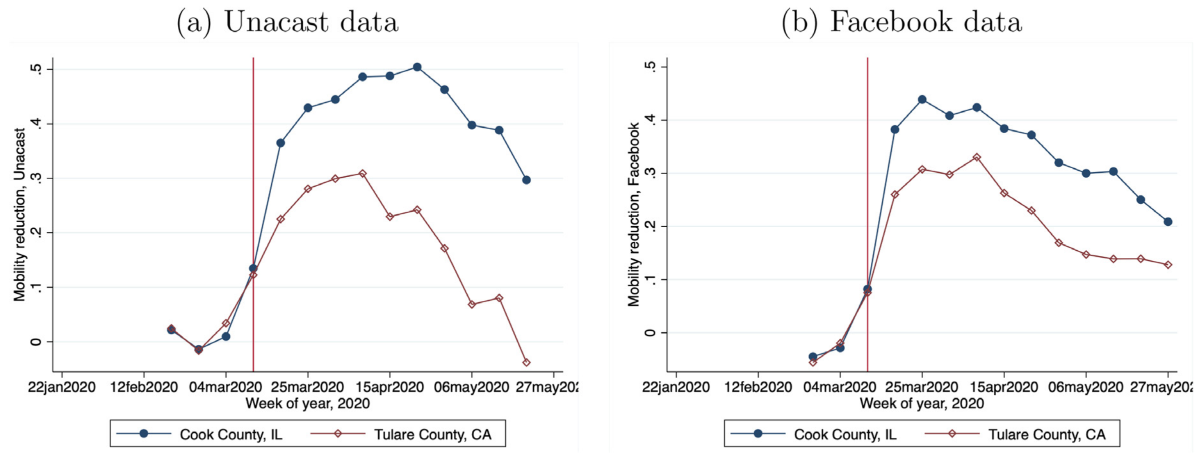

Fig. 4. Larger and more persistent mobility reduction in Cook County than in Tulare County, Week 9–21. *Note:* Panel (a) plots the proportional reduction in average distance travelled each day for residents of Cook County, IL and Tulare County, CA in the week listed on the x-axis relative to average distance traveled compared to the same day of the week in the four weeks before March 8, 2020, using Unacast data. Panel (b) shows the proportional reduction in the average number of 0.6km square tiles visited each day for residents of Cook County, IL and Tulare County, CA in the week listed on the x-axis compared to the same day of the week in February 2020, using Facebook data. Week 9 is from Feb 26 to March 3, and Week 21 is from May 20 to May 26. The solid vertical line is at Week 11, when a national emergency was announced in the U.S.

Table 2
Mobility data summary statistics.

Source	Country	Moment	Value
Unacast	U.S.	# of counties	3,054
		Mean (s.d.) of decline in mobility, Week 9–21	−0.19 (0.17)
Facebook	U.S.	# of counties	2,691
		Mean (s.d.) of decline in mobility, Week 9–21	−0.13 (0.14)
	Mexico	# of *municipios*	1,082
		with exposure to U.S. measure	1,012
		Mean (s.d.) of decline in mobility, Week 9–21	−0.21 (0.15)

Sources: Unacast and Facebook Data for Good. Unacast data covers 3,054 U.S. counties, while the coverage of the Facebook data varies by week (see Appendix Table A2 for details). Week 9 is from Feb 26 to March 3, and Week 21 is from May 20 to May 26.

of the week during the four weeks before March 8, 2020 (prior to the outbreak). As shown in Table 2, the measure covers 3,054 counties in the U.S., with an average decline in mobility of 19% during the period of Week 9 to Week 21.[24]

Our second mobility measure is from Facebook's Data for Good program.[25] The dataset uses the location information of users who enable location services on their mobile Facebook app. Our preferred mobility metric is the proportional change in the average number of 0.6 km by 0.6 km tiles visited during a 24 hour period compared to same day of the week in February 2020 (excluding President's day).[26] As shown in Table 2, the data cover 2,691 counties in the U.S. and 1,082 *municipios* in Mexico, since only regions with more than 300 unique users are included. During the period of Week 9 (Feb 26 to March 3) to Week 21 (May 20 to 26), the average decline in mobility in the U.S. is 13%, and the decline in Mexico is 21%.[27]

Places in the U.S. vary in the extent of social distancing. We measure social distancing based on the observed mobility reduction, with more positive values corresponding to larger declines in mobility. Figure 4 uses Cook County in Illinois (solid circles) and Tulare County in California (hollow diamonds) as an example. The reduction in mobility is more pronounced

[24] There are two filters applied to the sample to ensure data reliability. Unacast define a "dwell" as a set of location records observed within 80 m of each other within an 8-minute to 4-hour time period. Only devices with at least two dwells per day or one dwell longer than three hours in duration are included in the analysis. The data also exclude counties with population less than 1000 or that did not have at least 100 devices on at least 70% of the days during the pre-outbreak period.

[25] Source: https://dataforgood.fb.com/docs/covid19/.

[26] Details of the tile system are available at: https://docs.microsoft.com/en-us/bingmaps/articles/bing-maps-tile-system. The Facebook data include an alternative mobility measure indicating any time spent away from home each day (see Holtz et al., 2020). Our main analysis uses the change-in-tiles-visited metric for comparability with the Unacast mobility measure. However, in Appendix Table B9 we document very similar results with the stay-home measure.

[27] The Facebook data may represent a younger and somewhat more urban portion of the population. For the U.S., according to the Pew Research Center, in 2021, 77 percent of people 30–49 years old, 73 percent of people 50–64, and 50 percent of those 65 and older used Facebook. 70 percent of urban residents and 67 percent of rural residents used Facebook. See https://www.pewresearch.org/internet/fact-sheet/social-media/. Although similar measures are not available for Mexico, we expect a similar sample to be available there as well.

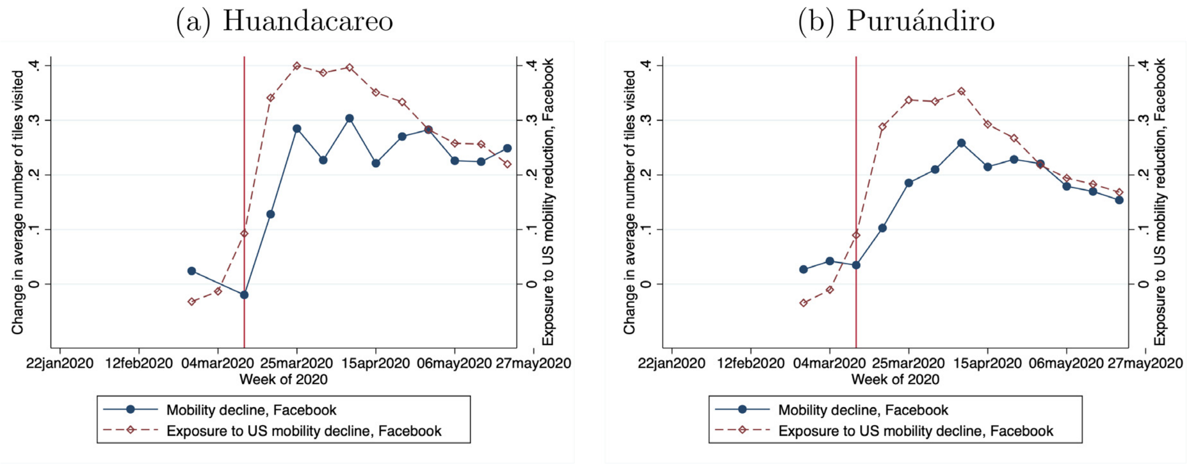

Fig. 5. Trends in social distancing in Huandacareo and Puruándiro, Mexico and their exposure to U.S. mobility declines. *Note:* Solid line and solid circles plotted on the left y-axis are the proportional reduction in the average number of 0.6 km square tiles visited each day for residents of Huandacareo, Michoacán (panel a) and Puruándiro, Michoacán (panel b) in the week listed on the x-axis compared to the same day of the week in February 2020, using Facebook data. Dashed line and hollow diamonds plotted on the right y-axis are the exposure to U.S. mobility declines defined in Eq. (1), using the Facebook data. Week 9 is from Feb 26 to March 3, and Week 21 is from May 20 to May 26. The solid vertical line is at Week 11, when a national emergency was announced in the U.S.

and persistent in Cook County than in Tulare County. In the Unacast data (Panel a) both counties started around zero in Week 10 (March 4 to 10), and by Week 12 (March 18 to 24), the decline in mobility was 37% in Cook County and 23% in Tulare County. In Week 21 (May 20 to 26), Cook County's mobility reduction declined to 30%, while in Tulare County it fell just below zero, indicating no reduction in mobility compared to the pre-pandemic period. Although the differences are less extreme in the Facebook data (Panel b), mobility in Cook County clearly decreased far more than in Tulare County in each week. Appendix Figure A3 maps the increase in social distancing from Week 9 to Week 21 for all U.S. counties in the Unacast and Facebook datasets, documenting substantial variation in social distancing behavior across counties.

Our Facebook data also cover mobility in Mexican *municipios*. Figure 5 shows the trends in social distancing (solid circles, left y-axis) in Huandacareo (Panel a) and Puruándiro (Panel b), the two *municipios* in Michoacán considered in Fig. 3. Social distancing in Mexico lagged that of the U.S. by a few weeks, consistent with the somewhat later emergence of the pandemic in Mexico. Huandacareo and Puruándiro exhibit substantial reductions in mobility by Week 13 (March 25 to 31), with both experiencing more than 20 percent reductions in mobility by Week 15 (April 8 to 14). As we will discuss below, the observation that Huandacareo exhibits more social distancing than Puruándiro is consistent with the fact that migrants from Huandacareo, who tend to migrate to Chicago, were exposed to more social distancing in the U.S. than migrants from Puruándiro, who tend to migrate to California's Central Valley.

3.3. Mexican exposure to U.S. social distancing

Intuitively, if a *municipio* happened to have more migrants residing in a U.S. county where more social distancing measures were taken, the migrants' relatives and friends remaining in that *municipio* may have received more information about the severity of Covid-19 and the importance of social distancing, and may have further transmitted this information to other residents of the *municipio*. Thus, we measure a Mexican *municipio*'s exposure to U.S. social distancing practices as follows:

$$exposure^s_{it} = \sum_j \frac{m_{ij}}{\sum_{j'} m_{ij'}} socdist^s_{jt}, \tag{1}$$

where m_{ij} is number of MCAS cards issued to migrants from *municipio* i living in county j in 2019, $socdist^s_{jt}$ is the social distancing measure in county j week t using data sources $s \in$ {Facebook,Unacast}. In our main analysis, we reduce noise by using the principal component of the two social distancing measures, denoted as $exposure^{pc}_{it}$, but our results are robust to using either data source individually (see Appendix B.4.1).

Figure 6 maps the change in the exposure measure in (1) for each Mexican *municipio* from Week 9 (Feb 26 to March 3) to Week 21 (May 20 to 26), using the Unacast data. This exposure measure ranges from −0.05 to 0.49, and the mean is 0.2 indicating that migrants lived in U.S. counties with a 20 percentage-point average decline in mobility from Week 9 to Week 21. Variation in exposure derives from a combination of the variation in social distancing across U.S. counties, shown in Fig. 4 and Appendix Figure A3, and the variation in the migrant destination distribution across *municipios*, shown in Fig. 3. These two sources of variation lead to significant differences in exposure to U.S. social distancing across *municipios*, and our empirical analysis will examine how this exposure influenced social distancing behavior in Mexico.

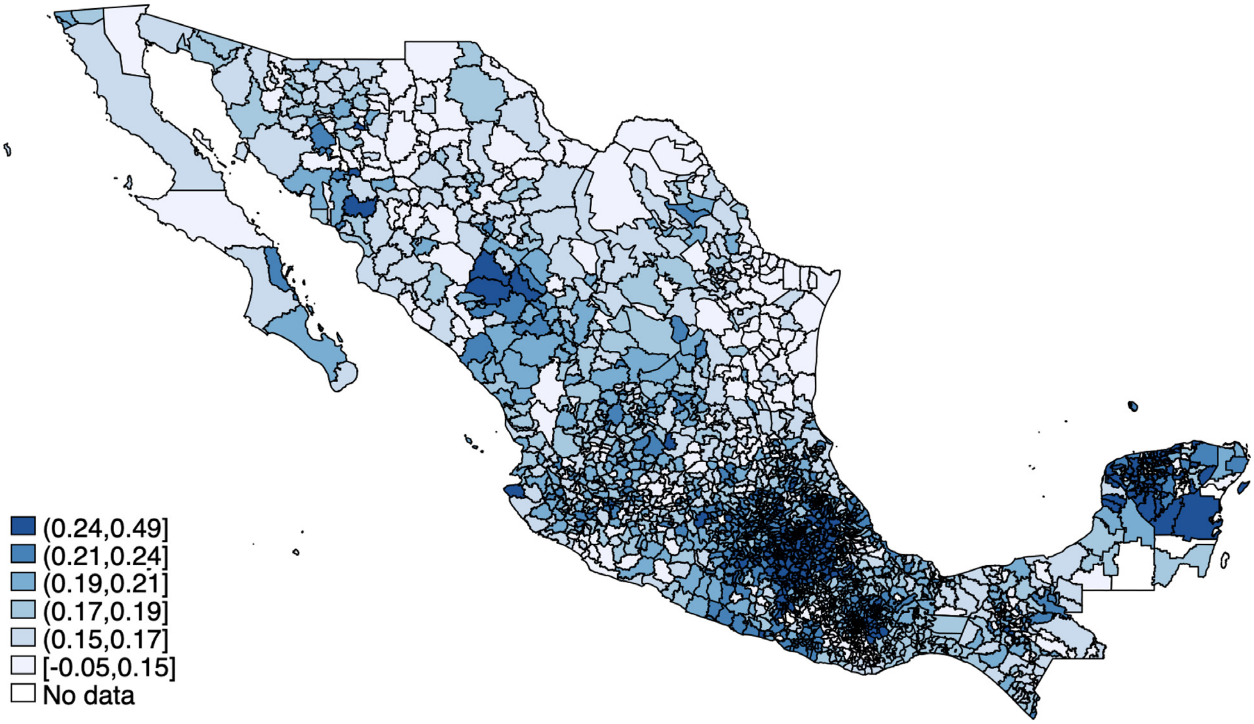

Fig. 6. Change in exposure to U.S. social distancing, Week 9 to Week 21. *Note:* The change in exposure to U.S. social distancing is calculated as $exposure^{Unacast}_{i,21} - exposure^{Unacast}_{i,9}$, using the Unacast data, where $exposure^{s}_{i,t}$ is defined in Eq. (1). Migrants from darker blue *municipios* were concentrated in U.S. counties exhibiting larger declines in mobility, while those from lighter blue locations faced smaller U.S. mobility declines. See Appendix Figure A2 for versions using Facebook or the principal component of the Unacast and Facebook measures together. Week 9 is from Feb 26 to March 3, and Week 21 is from May 20 to May 26. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Returning to Fig. 5, we plot the exposure measure (hollow diamonds, right y-axis) for Huandacareo (Panel a) and Puruándiro (Panel b). Because Huandacareo's migrants concentrate in Cook County (Chicago), which had a large increase in social distancing, and Puruándiro's migrants concentrate in Tulare County (CA Central Valley), which had much less social distancing, Huandacareo was exposed to a larger U.S. mobility decline throughout the pandemic period. A *municipio*'s mix of migrant destinations combines with variation in social distancing behavior across U.S. counties to create variation in exposure to U.S. social distancing, as measured in (1). After being more exposed to more U.S. social distancing through its migrant network, Huandacareo exhibited larger declines in mobility than Puruándiro. As we will document below, this relationship between U.S. and Mexican social distancing holds on average across *municipios*.

3.4. Other datasets

We use various data sources to measure characteristics of U.S. counties and Mexican *municipios* that may have affected disease or information transmission. The number of weekly Covid-19 cases and deaths by U.S. county comes from John Hopkins University, and the corresponding information for Mexico come from the Mexican Ministry of Health.[28] Paralleling our measure of exposure to U.S. social distancing, we also construct *municipio* i's exposure to U.S. Covid-19 cases as follows.

$$exposure^{case}_{it} = \sum_j \frac{m_{ij}}{\sum_{j'} m_{ij'}} \left(\frac{\text{cumulative cases}_{jt}}{\text{population}_{jt_0}} \right), \tag{2}$$

where $\text{cumulative cases}_{jt}$ is the cumulative number of cases in county j and week t, and population_{jt_0} is the county population in 2010 (in 100,000 unit), using the 2010 Census.[29] The measure in (2) therefore captures the average cumulative case rate faced by U.S. migrants from *municipio* i. Note that the main analysis uses case rate controls (both for the number of local cases in Mexico and the exposure to U.S. cases) lagged by one week to avoid potential reverse causality in which

[28] *Sources:* https://coronavirus.jhu.edu/ and https://coronavirus.gob.mx/, respectively.

[29] In Appendix B.2.1 we present analyses using an alternative case measure based on the inverse hyperbolic sine transformation, finding very similar results.

current social distancing affects contemporaneous case rates. The results are nonetheless robust to using contemporaneous case controls (Appendix B.2.3).

Pre-pandemic U.S. county characteristics are from the 2010 Census and 2005–2009 American Community Surveys (ACS). Specifically, we use the 2010 Census to calculate the county-level Hispanic or Latino share of the population, the Mexican population share, total population, and land area (used to calculate population density). We use the 2005–2009 ACS to calculate the county-level 1) number of Hispanic and Latino individuals aged 25 and over by educational attainment, and similar numbers for the overall population; 2) number of Hispanic and Latino families by income group; and 3) mean and median household income in the entire population.

Mexican *municipio* characteristics are from the 2015 Intercensal Count (*Conteo*), including the share of working age population (aged 16 to 65), schooling attainment, share employed, and income earned in the working age population.[30] We obtain population density and percent of urban population from Mexican Statistical Office (INEGI) tabulations. We use two measures of initial remittance intensity by *municipio*: 1) 2019 remittance value per capita using quarterly remittance data from the Mexican Central Bank (note that higher frequency remittance data are not available, so we can not observe week-to-week changes in remittances) and 2) the 2015 share of *municipio* households that received any remittances from abroad using the 2015 Intercensal Count (*Conteo*).

The timing of stay-at-home orders in U.S. states is obtained from Raifman et al. (2020), and similar data for Mexican states were assembled from Mexican states' official decrees (see Appendix A.7 for details).

4. Social learning across borders: Main empirical results

4.1. Empirical specification

Our empirical analysis examines the impact of exposure to U.S. social distancing practices on social distancing in Mexican *municipios*, and seeks to isolate the portion of that impact driven by social learning. Our baseline estimation equation is as follows:

$$socdist_{it} = \alpha + \beta exposure_{it}^{pc} + \Gamma z_{it} + I_i + I_t + \epsilon_{it}, \tag{3}$$

where $socdist_{it}$ is the mobility reduction in *municipio* i week t using the Facebook data, and $exposure_{it}^{pc}$ measures exposure to U.S. social distancing in the same week, following Eq. (1) using the principal component of Unacast and Facebook mobility measures (Appendix B.4.1 shows similar results using each measure separately). We include a variety of *municipio*-week-specific controls z_{it} to take into account time-varying region-specific factors that could affect people's social distancing behavior, such as the severity of the local disease outbreak. *Municipio* fixed effects I_i are included to control for *municipio*-specific factors such as population density, income level, education level, and means of transportation to work. Week fixed effects I_t are used to account for national policies that affect social distancing behaviors across all regions in a week. We cluster standard errors at the *municipio* level.

The parameter β captures the relationship between U.S. social distancing behaviors and network-connected Mexican *municipios*' social distancing practices. A positive value of β indicates that *muncipios* connected to U.S. counties practicing more social distancing experienced on average larger reductions in mobility. In order to interpret β as the causal effect of U.S. social distancing on Mexican social distancing, the key identification assumption is that changes in social distancing behaviors across Mexican *municipios* with similar observable characteristics would not have differed systematically in the absence of differential exposure to U.S. social distancing practices.

This identification assumption may be violated if, for example, Mexican regions with higher population density tend to send more migrants to U.S. counties with higher population density. Since the probability of infection is higher in denser areas, people in both regions may practice more social distancing even in the absence of information transmission. A similar issue may arise if migrant origins and destinations are selected along other dimensions that affect the severity of the local Covid-19 outbreak. We refer to this as the "migrant sorting" channel and rule out its effects on our estimates by including extensive controls flexibly capturing the effects of relevant regional characteristics over time.

Another threat to causal interpretation would arise if more exposed *municipios* had different trends in mobility even before the outbreak. However, as seen in Figs. 4 and 5, both U.S. and Mexican mobility reductions were very close to zero in Week 9 compared to the pre-Covid period (recall that our mobility measures reflect proportional changes relative to the pre-Covid period). This is not particular to the regions examined in those figures; the mean mobility reduction across *municipios* was 0.004 in Week 9 (standard deviation 0.05). Thus, pre-Covid social distancing trends were nearly identical and approximately equal to zero across *municipios* (see Appendix Table A5). The absence of confounding pre-trends is shown even more directly in Panel (a) of Fig. 7, which relates the change in *municipio* mobility from Week 9 to Week 11 (prior to substantial outbreaks in the U.S. or Mexico) to the change in exposure to U.S. social distancing from Week 11 to Week 21 (during the period of outbreaks). The lack of an economically or statistically significant relationship in Panel (a) indicates that *municipios* that would later face larger vs. smaller changes in U.S. social distancing had similar changes in mobility prior to the start of the outbreak period.

[30] Source: IPUMS International (Minnesota Population Center, 2020).

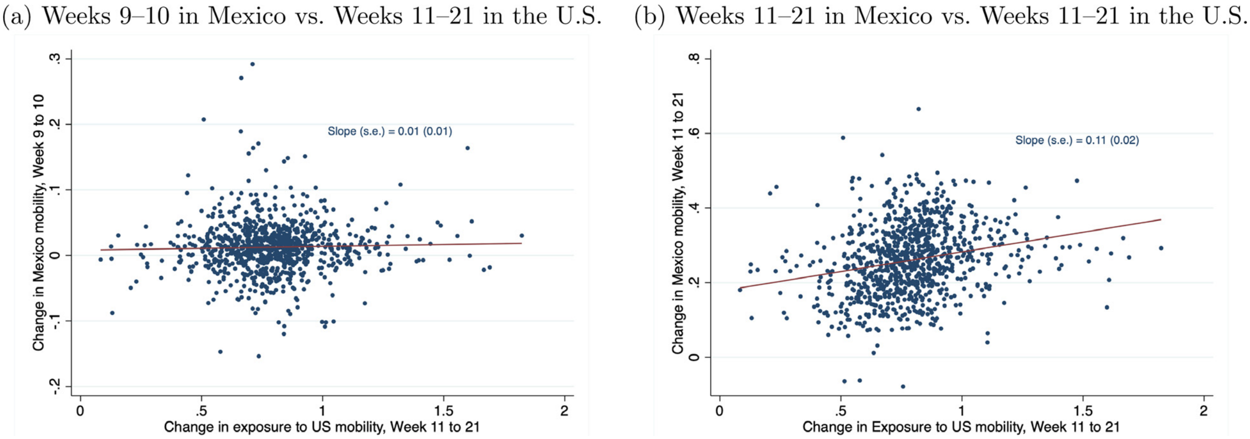

Fig. 7. Correlation between changes in social distancing in Mexico and the U.S. *Note:* This figure includes all Mexican *municipios* with at least one Covid-19 case by Week 21, and each point represents a *municipio*. In both panels, the horizontal axis is the change in exposure to U.S. social distancing from Week 11 to Week 21 ($exposure^{pc}_{i,21} - exposure^{pc}_{i,11}$). In Panel (a), the vertical axis is the change in social distancing from Week 9 to Week 10 ($socdist_{i,10} - socdist_{i,9}$), prior to substantial Covid outbreaks in the U.S. or Mexico. The lack of relationship in Panel (a) indicates the absence of confounding pre-trends. In Panel (b), the vertical axis is the change in social distancing from Week 11 to Week 21 ($socdist_{i,21} - socdist_{i,11}$). The substantial relationship in Panel (b) reflects our main finding that *municipios* facing larger U.S. mobility declines exhibited more social distancing during the pandemic period (following Week 11). The mean (s.d.) is 0.80 (0.21) for the x-axis, is 0.01 (0.04) for the y-axis in panel (a), and is 0.26 (0.10) for the y-axis in panel (b). Week 9 is from Feb 26 to March 3, Week 11 is from March 11 to March 17, and Week 21 is from May 20 to May 26.

A positive estimate of β may also reflect the effects of disease transmission rather than information transfer along migrant networks. If disease transmission operates along the migration network, then migrant-connected locations in the U.S. and Mexico will have similar severity and timing of outbreaks and may have similar degrees of social distancing as a result. Although a result driven by this "disease transmission" channel could potentially be interpreted as a causal effect of exposure to the U.S. outbreak, it would not reflect the information channel of interest. In order to rule out this disease transmission channel, we include flexible controls for the severity of the local outbreak in the *municipio* and in network-connected U.S. counties (following (2)).

Finally, changing remittances could potentially influence the relationship between U.S. and Mexican social distancing behavior. If U.S. regions exhibiting larger increases in social distancing also experience larger declines in economic activity, migrants living in those regions may reduce their remittance payments, leading to less economic activity and perhaps less mobility in their source regions in Mexico. We rule out this channel in a variety of ways. Prior work has shown that declining U.S. labor markets do indeed lead to reduced remittance payments to migrant-connected source regions, but that this reduction in remittance income tends to *increase* labor supply in affected *municipios*, which if anything would increase mobility rather than reduce it (Caballero et al., 2020). In practice, national remittances continued growing at roughly constant rate during the pandemic, with no sign of a substantial decline (Appendix Figure A4). While these observations imply that the remittance channel was unlikely to explain our findings, we nonetheless control flexibly for two measures of each *municipio*'s reliance on remittances: the 2019 remittance value per capita and the 2015 share of households receiving remittances from abroad.[31] Including these controls has minimal effect on the relationship between U.S. and Mexican social distancing behavior, further ruling out the remittance channel as an important mechanism relating Mexican and U.S. social distancing.

4.2. Main results

Before reviewing the main estimation results from Eq. (3), we present visual evidence on the unconditional relationship between Mexican social distancing and declines in mobility in migrant-connected U.S. counties. For each *municipio i,* we calculate the long-difference change in local social distancing ($socdist_{i,21} - socdist_{i,11}$) and the change in the *municipio's* exposure to U.S. social distancing ($exposure^{pc}_{i,21} - exposure^{pc}_{i,11}$) from Week 11 to Week 21. Panel (b) of Fig. 7 shows a scatter plot relating these two measures, where each point represents a *municipio*. The fitted line has a slope of 0.11 (significant at the 1% level), indicating that a one-standard-deviation larger increase in exposure to U.S. social distancing is associated with a 0.23-standard-deviation larger decrease in Mexican' mobility.

We now turn to the main specification in Eq. (3) to investigate cross-border learning about social distancing. Table 3 shows the estimation results. Columns (1)–(4) only include *municipios* with at least one case by Week 21, and Columns (5)–

[31] We control for the *municipio*'s initial reliance on remittances rather than the change in remittances across weeks because weekly remittance data are not available for any level of geographic aggregation in Mexico.

Table 3
Larger exposure to U.S. social distancing led to more social distancing in Mexico, Week 9 to Week 21.

Outcome: Mexico social dist.	(1) *Municipios* with cases > 0	(2)	(3)	(4)	(5) All *municipios*	(6)	(7)	(8)
Exposure to U.S. social distancing	0.055***	0.050***	0.050***	0.046***	0.052***	0.046***	0.047***	0.043***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Exposure to U.S. cases, lagged one week		0.004**		0.002*		0.004***		0.003**
		(0.001)		(0.001)		(0.001)		(0.001)
Cumulative cases in *municipio*, lagged one week			0.062***	0.061***			0.066***	0.066***
			(0.011)	(0.011)			(0.011)	(0.011)
Constant	0.213***	0.208***	0.206***	0.204***	0.207***	0.203***	0.201***	0.199***
	(0.000)	(0.002)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.002)
Observations	11,989	11,989	11,989	11,989	13,865	13,865	13,865	13,865
R-squared	0.914	0.914	0.920	0.920	0.908	0.908	0.914	0.914

Note: Documents larger increases in social distancing in Mexican *municipios* whose U.S. migrants live in locations exhibiting larger increases in social distancing, using the U.S. social-distancing exposure measure in (1). Columns (1)–(4) include *municipios* with at least one Covid-19 case by the end of Week 21, and Columns (5)–(8) include all *municipios*. All specifications include week fixed effects and *municipio* fixed effects. The case measures for the U.S. and Mexico are the number of cumulative cases per 100,000 population. In the first four columns, the mean (s.d.) of Mexican social distancing is 0.21 (0.15), of exposure to U.S. social distancing is 0.01 (1.4), of lagged U.S. cases is 1.1 (1.4), and of lagged *municipio* cases is 0.1 (0.3). The corresponding numbers for the last four columns are 0.21 (0.15), 0.01 (1.4), 1.1 (1.4), and 0.1 (0.3). Standard errors clustered at the *municipio* level are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(8) include all *municipios*.[32] In Column (1), we regress social distancing in Mexican *municipios* on the exposure to U.S. social distancing ($exposure_{it}^{pc}$), controlling for *municipio* fixed effects and week fixed effects. The coefficient is 0.055 (statistically significant at the 1% level), indicating that a one standard deviation larger exposure to U.S. social distancing (1.4) led to a 0.51 standard deviation larger increase in social distancing in Mexico.[33] Column (5) uses the same specification for all *municipios*. The coefficient is 0.052, which is smaller than the Column (1) estimate, suggesting that the learning effect is weaker in areas with no active Covid-19 cases (confirmed directly in Appendix B.7).[34]

In Columns (2)–(4) and (6)–(8), we introduce controls for the cumulative numbers of cases in the relevant *muncipio* or in the U.S. destinations to which it is connected via the migrant network, using the measure in Eq. (2). Case controls are lagged by one week to avoid potential reverse causality in which current social distancing affects contemporaneous case rates. As expected, when the local outbreak is more severe, people in Mexico practice more social distancing.[35] Exposure to U.S. outbreaks also increases Mexican social distancing, although the effect is an order of magnitude smaller than that of local outbreaks. Importantly, the estimated effect of exposure to U.S. social distancing is essentially unchanged when including these controls for the number of cases in Mexico and the U.S. This finding rules out the disease transmission channel discussed in the prior subsection. If the observed correlation between U.S. and Mexican social distancing were the result of disease transmission along the migrant network, the inclusion of these controls would absorb the variation driving the observed correlation, and our results would disappear.

Although disease transmission is not an important mechanism driving the relationship between U.S. and Mexican social distancing behavior, it remains possible that correlated social distancing behavior results from underlying similarities in migrants' source and destination regions – what we have called the "migrant sorting" channel. For example, concurrent research finds that individuals and regions with higher education levels and higher incomes are more likely to practice social distancing (Brzezinski et al., 2020, Wright et al., 2020, Mongey et al., 2021, and Fan et al., 2020, among others). If migrants from higher income areas of Mexico are more likely to choose higher income destinations in the U.S., then one might observe correlated social distancing even without information transmission. Although our inclusion of *municipio* fixed effects addresses level differences in social distancing, it does not capture the possibility that higher income locations (for example) *increasingly* practice social distancing as the pandemic evolves.

We address this migrant sorting concern in Table 4. First, we measure *municipio* features that the literature has shown are correlated with baseline social distancing behavior, including population density, urban population share, working-age population share, average years of education, mean log income, and the employment to working age population ratio. Then,

[32] For details on the sample restrictions, see Appendix A3.

[33] Appendix Table B7 shows results using the Facebook mobility data alone, which allows us to compare the magnitudes of our findings to those of Holtz et al. (2020) on social-distancing spillovers across U.S. counties. Columns (1)–(4) of Table B7 imply that a 10 percent increase in U.S. social distancing increased Mexican social distancing by 3.0 to 3.7 percent. The comparable estimate in column (1) of Table S8 in Holtz et al. (2020) is four times larger, implying that a 10 percent increase in social distancing in other counties increases social distancing by 17 percent in the focal county. This difference seems reasonable, particularly given that local and other domestic spillovers are likely to be much larger than those operating across countries.

[34] These estimates are smaller than the slope coefficient in Panel (b) of Fig. 7 because the Figure only uses data from Week 11 and Week 21 to calculate a long difference. It is evident from Fig. 4 that U.S. social distancing was strongest around Week 15 and declined afterwards. However, during the same period, Mexican social distancing did not decline much. Thus, when using the full panel of Week 9 to Week 21 the changes in U.S. social distancing are larger, so the coefficient estimate on exposure is smaller.

[35] Similarly, Brzezinski et al. (2020) find that in the United States, people engage in social distancing even in the absence of lockdown policies, once the virus occurs in their area.

Table 4
The main results are robust to controlling for differential effects of socio-economic conditions across weeks.

Variable for interaction	(1) population density	(2) % urban	(3) % age 16–65	(4) years of education	(5) log income	(6) % employed	(7) remit. per capita, 2019	(8) % hh remit. > 0, 2015
Exposure to U.S. social distancing	0.045***	0.043***	0.043***	0.040***	0.057***	0.045***	0.042***	0.042***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Week 10 Interaction	0.002***	0.013**	0.124***	0.004***	0.016***	0.065***	−0.009***	−0.063***
	(0.000)	(0.005)	(0.041)	(0.001)	(0.004)	(0.024)	(0.003)	(0.024)
Week 11 Interaction	0.005***	0.052***	0.351***	0.010***	0.049***	0.165***	−0.005*	−0.085***
	(0.001)	(0.007)	(0.054)	(0.001)	(0.006)	(0.038)	(0.003)	(0.032)
Week 12 Interaction	0.010***	0.112***	1.029***	0.028***	0.117***	0.428***	-0.019***	-0.200***
	(0.001)	(0.009)	(0.066)	(0.002)	(0.007)	(0.041)	(.005)	(0.038)
Week 13 Interaction	0.012***	0.096***	1.042***	0.027***	0.098***	0.365***	−0.033***	−0.259***
	(0.001)	(0.009)	(0.061)	(0.002)	(0.007)	(0.036)	(0.005)	(0.035)
Week 14 Interaction	0.014***	0.102***	1.100***	0.028***	0.095***	0.404***	−0.042***	−0.310***
	(0.001)	(0.010)	(0.067)	(0.002)	(0.007)	(0.037)	(0.004)	(0.037)
Week 15 Interaction	0.015***	0.118***	1.226***	0.032***	0.114***	0.443***	−0.046***	−0.351***
	(0.001)	(0.010)	(0.072)	(0.002)	(0.008)	(0.044)	(0.004)	(0.039)
Week 16 Interaction	0.014***	0.108***	1.137***	0.031***	0.100***	0.395***	−0.054***	−0.359***
	(0.001)	(0.010)	(0.073)	(0.002)	(0.008)	(0.040)	(0.005)	(0.040)
Week 17 Interaction	0.015***	0.104***	1.169***	0.031***	0.101***	0.371***	−0.057***	−0.394***
	(0.001)	(0.010)	(0.074)	(0.002)	(0.008)	(0.040)	(0.005)	(0.041)
Week 18 Interaction	0.016***	0.093***	1.123***	0.030***	0.094***	0.342***	−0.057***	−0.399***
	(0.001)	(0.011)	(0.078)	(0.002)	(0.008)	(0.042)	(0.006)	(0.044)
Week 19 Interaction	0.019***	0.100***	1.387***	0.034***	0.101***	0.386***	−0.074***	−0.508***
	(0.001)	(0.012)	(0.084)	(0.002)	(0.009)	(0.046)	(0.007)	(0.049)
Week 20 Interaction	0.019***	0.106***	1.427***	0.034***	0.099***	0.404***	−0.075***	−0.499***
	(0.001)	(0.012)	(0.081)	(0.002)	(0.009)	(0.048)	(0.006)	(0.048)
Week 21 Interaction	0.019***	0.095***	1.328***	0.031***	0.082***	0.363***	−0.077***	−0.524***
	(0.001)	(0.012)	(0.083)	(0.002)	(0.009)	(0.046)	(0.007)	(0.048)
Observations	11,989	11,989	11,989	11,951	11,951	11,989	11,989	11,989
R-squared	0.92	0.92	0.93	0.93	0.92	0.92	0.92	0.92

Note: Shows that the relationship between U.S. and Mexican social distancing in Table 3 is robust to allowing the effects of initial *municipio* characteristics to vary arbitrarily across weeks. Each column replicates the regression in Column (1) of Table 3, adding the interaction of a *municipio* characteristic with week fixed effects (week 9 is the omitted category). The relevant characteristics are shown in the column titles (see text for details). In addition to the interactions of the initial characteristic and week fixed effects shown in the table, all specifications include week fixed effects and *municipio* fixed effects. The sample includes *municipios* with at least one Covid-19 case by the end of Week 21 and for which the initial characteristic measure is available. Appendix Table B15 shows the results are robust to omitting the positive case count restriction, and Appendix Table B10 shows the results are robust to including all characteristic interactions together in a single regression. Standard errors clustered at the *municipio* level are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

we control for each feature interacted with separate indicators for each week of our sample, allowing for the effect of the relevant feature to vary arbitrarily over time. As an example, Column (1) interacts the initial population density with week indicators, controlling for the possibility that migrants from more densely populated *municipios* choose to live in more densely populated counties. Across the columns of Table 4, it is apparent that the six regional features generally drive growing gaps in Mexican social distancing between Week 9 and Week 12, after which the effects are largely stable. Most importantly for our purposes, the effect of exposure to U.S. social distancing is very stable when comparing the estimates in Table 4 to those in Columns (1)–(4) of Table 3.[36] Appendix Table B10 shows nearly identical results when controlling for all six characteristic-week interactions together in one specification, and Appendix B.5.2 finds similarly consistent results when controlling for a wide array of additional initial *municipio* characteristics. Together, these findings rule out the effects of migrant sorting based on this wide array of location characteristics.

Another potentially important regional characteristic is the share of jobs that facilitate working from home. In Appendix Section B.5.3, we use the industry-level measure of the ability to work from home constructed by Dingel and Neiman (2020), and the industry mix of local employment in the 2015 Intercensal Count to construct the share of jobs in each Mexican *municipio* that facilitate working from home. We repeat the analysis in Table 4 by using the interaction of this share with week fixed effects, finding that the effect of exposure to U.S. social distancing remains unchanged. Thus, as with the characteristics examined in Table 4, this regional characteristic is not likely to drive the relationship between U.S. and Mexican social distancing through migrant sorting.

Table 4 also addresses the remittance channel by introducing flexible controls for the *municipio*'s initial reliance on remittances. If changing remittances were driving the observed relationship between U.S. and Mexican social distancing, *municipios* that initially relied more heavily on remittances should have been more affected as remittances declined following the onset of the pandemic. Column (7) flexibly controls for this possibility by interacting week indicators with the share of

[36] Table 4 uses only *municipios* with a positive case count by Week 21, but we find similar agreement when using all *municipios* - see Appendix Table B15.

local households receiving any remittances in 2015, while Column (8) interacts with the value of remittances per capita in 2019. In both cases, the interaction coefficients are negative, implying lower levels of social distancing in *municipios* with stronger reliance on remittances. This finding is consistent with the fact that both remittance measures are negatively correlated with the characteristics in Columns (1)–(6).[37] If the remittance channel were driving our results, we would expect a substantial change in the coefficient on exposure to U.S. social distancing. Instead, we continue to find a very stable relationship as in the other columns of Table 4, ruling out the importance of the remittance channel as a primary driver of our results.

Along with those already mentioned, in the appendix we present a wide variety of additional robustness tests confirming the findings in Tables 3 and 4. This includes using an alternative functional form or alternative timing for the case controls (Appendix B.2), controlling for stay-at-home orders in Mexico (Appendix B.3), and using alternative mobility measures (Appendix B.4), among many others. In all cases, the results presented here are confirmed, and all specification checks yield favorable results.

Together, the various results and robustness tests in this section document a strong and robust relationship between social distancing behavior in the U.S. and reductions in mobility in migrant-connected regions in Mexico. This appears to be a causal relationship that was not driven by disease transmission, migrant sorting between similar regions in the U.S. and Mexico, or changing remittances. Instead, the results support the conclusion that receiving information about social distancing from acquaintances, friends, and family living in the U.S. led to increased social distancing in Mexico.

5. Heterogeneous effects by origin and destination characteristics

Information transmission and social learning depend not only on the information content itself, but also crucially on how the information is spread and who communicates with whom. For example, BenYishay and Mobarak (2019) show that the social standing of the communicators matters in the process of promoting agricultural technology adoption, and that people who share the same group identity and face comparable agricultural conditions are especially influential. Büchel et al. (2020) show that in migrant networks, local contacts who migrated recently or are more central in the social network have larger impacts on reducing information frictions. In the context of the Covid-19 pandemic, Fan et al. (2020) find that there are substantial gaps in behaviors and beliefs across gender, income, and political party lines. These gaps may also influence the effects of information transmission. In this section, we therefore investigate heterogeneity in the effect of exposure to U.S. social distancing based on the characteristics of Mexican *municipios* and of connected U.S. counties.

5.1. Origin characteristics

We first focus on origin characteristics. As an example, even when facing the same exposure to U.S. social distancing, people living in a *municipio* with higher average educational attainment may react differently than those in a less educated area. Brzezinski et al. (2020) find that those in locations with higher average educational attainment have less distrust in science and adopt more social distancing. We test for heterogeneity along this and other dimensions by interacting various pre-pandemic *municipio* characteristics with the exposure measure in Eq. (1). The regression specification is as follows.

$$socdist_{it} = \alpha + \beta \ exposure^{pc}_{it} + \gamma \ exposure^{pc}_{it} \times C_i + I_i + I_t + \epsilon_{it}, \tag{4}$$

where C_i is a time-invariant baseline characteristic of *municipio* i, including population density, urban share of population, share of working age population, average years of education, log earnings per person, share employed, remittance value per capita, and the share of households receiving remittances. Note that the *municipio* fixed effects, I_i, capture the level effect of the characteristic C_i. To interpret the size of the heterogeneous effects, we first evaluate the impact of the exposure to U.S. social distancing ($exposure^{pc}_{it}$) at the mean value of C_i and call it $\hat{\beta}_1$. Then we evaluate the effect at the mean plus one-standard deviation of C_i and call it $\hat{\beta}_2$. Finally, we compare the two by calculating $\hat{\delta} = \hat{\beta}_2/\hat{\beta}_1 - 1$. A more positive value of $\hat{\delta}$ indicates that more positive values of C_i drive more positive effects of U.S. social distancing on Mexican social distancing.[38]

Generally, Table 5 finds that *municipios* with more favorable socio-economic conditions responded more strongly to U.S. social distancing. For example, Column (1) evaluates the heterogeneous effect by population density. Compared to the effect on a *municipio* with average population density, the effect is 6% larger when the population density is one-standard deviation larger. We find similar heterogeneity when considering the urban population share (15%), working age population share (16%), average years of schooling (21%), log average earnings (14%), and employment share (16%).[39] In Appendix B.6.1, we find similar increases in social distancing responses in places where a larger share of the workforce is able to work from home, consistent with Dingel and Neiman (2020)'s finding that regions with higher incomes also have higher shares of jobs in which working home is feasible. Columns (7) and (8) investigate heterogeneity based on the *municipio*'s initial reliance

[37] See Appendix Section A.9 for details.

[38] The expressions for $\hat{\beta}_1$ and $\hat{\beta}_2$ are as follows: $\hat{\beta}_1 = \hat{\beta} + \hat{\gamma}\bar{C}$, and $\hat{\beta}_2 = \hat{\beta} + \hat{\gamma}(\bar{C} + sd(C))$, where $\bar{C}$ is the mean of C_i, and $sd(C)$ is the standard deviation of C_i.

[39] The interaction coefficients in Table 5 remain significant at the 1 percent level when implementing a conservative Bonferroni correction for multiple testing across the 8 specifications.

Table 5
Municipios with more favorable socio-economic conditions responded more strongly to U.S. social distancing.

Outcome: Mexico social dist.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to US social dist.	0.049***	0.030***	−0.114***	−0.013	−0.144***	−0.001	0.052***	0.056***
	(0.007)	(0.007)	(0.011)	(0.008)	(0.015)	(0.009)	(0.007)	(0.007)
Interact: population density	0.003***							
	(0.000)							
Interact: share urban		0.025***						
		(0.002)						
Interact: aged 16–65 share			0.263***					
			(0.014)					
Interact: yrs of schooling				0.007***				
				(0.000)				
Interact: log income					0.024***			
					(0.002)			
Interact: % employed						0.094***		
						(0.009)		
Interact: pc. remit 2019							−0.010***	
							(0.001)	
Interact: % hh remit 2015								−0.068***
								(0.008)
Constant	0.212***	0.212***	0.212***	0.212***	0.213***	0.212***	0.212***	0.212***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean (s.d.) of the interaction	0.58 (1.84)	0.61 (0.27)	0.62 (0.03)	8.6 (1.4)	8.4 (0.34)	0.52 (0.08)	0.42 (0.50)	0.13 (0.07)
$\hat{\delta}$	6%	15%	16%	21%	14%	16%	-10%	-10%
Observations	11,989	11,989	11,989	11,951	11,951	11,989	11,989	11,989
R-squared	0.917	0.917	0.921	0.921	0.920	0.918	0.916	0.916

Note: Documents more positive effects of U.S. social distancing on Mexican social distancing in *municipios* with more favorable socio-economic characteristics and less positive effects in *municipios* with stronger initial remittance exposure. Each column estimates Eq. (4), focusing on a different initial *municipio* characteristic in the interaction. All columns include week fixed effects and *municipio* fixed effects, with the latter capturing the level effects of the initial *municipio* characteristics. The sample includes *municipios* with at least one Covid-19 case by the end of Week 21 and for which the initial characteristic measure is available. Appendix Table B16 shows the results are robust to omitting the positive case count restriction. Standard errors clustered at the *municipio* level are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The p-values for the interaction term coefficients are all less than 0.00125 ($= 0.01/8$), so all remain significant at the 1 percent level even after a conservative Bonferroni correction.

on remittances, finding smaller responses to U.S. social distancing in places with larger baseline remittance exposure. This relationship is consistent with the negative correlation between remittances and the characteristics examined in Columns (1)–(6), and provides further evidence against the remittance channel as a driver of our main results.[40]

5.2. Destination characteristics

Migrant destination characteristics may also influence the information transmission process. In addition to the examples mentioned above, Kerr (2008) shows that ethnic ties to home countries among scientific and entrepreneurial communities in the U.S. facilitate international knowledge transfer. Mexican migrants in the United States may be more likely to learn from people with a similar background. For example, if a destination region has a larger Hispanic community or has a higher share of residents of Mexican descent, the connected *municipios* may learn from them more easily. Learning about social distancing may also be more effective if the destination regions' Hispanic population has higher socio-economic status. If Mexican migrants learn from the general population, then the average education and income level of U.S. counties may also be important.

In Table 6, we evaluate how the effect of exposure to U.S. social distancing differs by the average characteristics of migrant-connected destination regions. For a destination county characteristic x_j, we calculate the average value faced by migrants from *municipio* i as a migration-network weighted average as follows.

$$x_i = \sum_j \frac{m_{ij}}{\sum_{j'} m_{ij'}} x_j \tag{5}$$

We then estimate specifications paralleling Eq. (4), using x_i as the interaction variable. Table 6 finds that the effect of exposure to U.S. social distancing is statistically significantly influenced by the share of Hispanics and the share of population of Mexican descent (Columns 1 and 2), but the effects do not differ by the average Hispanic education, average education, the log of Hispanic income, and the log average income in U.S. destinations (Columns 3–6). This finding is consistent with the information transmission hypothesis. However, even in the first two columns, the extent of heterogeneity is quite small;

[40] If changing remittances drove the overall positive relationship between U.S. and Mexican social distancing, we would expect a positive interaction coefficient in Columns (7) and (8) of Table 5, indicating that remittance-dependent regions drive the overall positive relationship. Instead, we find the opposite.

Table 6
The effect of exposure to U.S. social distancing is stronger in *municipios* connected to U.S. destinations with a higher share of Hispanics and a higher share of Mexican origin.

Outcome: Mexico soc. dist.	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to U.S. soc. dist.	0.046***	0.051***	0.042	0.075***	0.020	0.050
	(0.008)	(0.007)	(0.033)	(0.025)	(0.080)	(0.073)
Interact: % Hispanic	0.024***					
	(0.007)					
Interact: % Mexican		0.026***				
		(0.007)				
Interact: Hispanic education			0.001			
			(0.003)			
Interact: education				−0.001		
				(0.002)		
Interact: log Hispanic income					0.003	
					(0.007)	
Interact: log income						0.000
						(0.007)
Constant	0.213***	0.213***	0.213***	0.213***	0.212***	0.213***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean (s.d.) of the interaction	0.30 (0.08)	0.23 (0.08)	10.3 (0.22)	13.0 (0.27)	10.9 (0.07)	11.2 (0.08)
$\hat{\delta}$	3.6%	3.7%	0.4%	−0.4%	0.4%	0%
Observations	11,989	11,989	11,989	11,989	11,989	11,989
R-squared	0.914	0.914	0.914	0.914	0.914	0.914

Note: Documents modest heterogeneity in the effects of U.S. social distancing on Mexican social distancing in *municipios* whose migrants typically locate in U.S. counties with different characteristics. Each column estimates a version of Eq. 4 in which the interaction term reflects the migration-network weighted average of U.S. destination characteristics, defined in (5). All columns include week fixed effects and *municipio* fixed effects, with the latter capturing the level effects of the initial weighted-average destination characteristic. The sample includes *municipios* with at least one Covid-19 case by the end of Week 21. Appendix Table B17 shows the results are robust to omitting the positive case count restriction. Standard errors clustered at the *municipio* level are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. When using a conservative Bonferroni correction (dividing critical p-values by 8), the first two interaction coefficients are significant at the 1 percent level.

using the same $\hat{\delta}$ measure described in the previous subsection, compared to the effect of exposure of a *municipio* with the average value of each characteristic, the effect is only 3.4–3.7% larger when the characteristic's value is one-standard deviation larger.[41]

In sum, we primarily find heterogeneity in learning based on origin characteristics. More affluent Mexican *municipios* responded more strongly to exposure to U.S. social distancing, while *municipios* with more exposure to remittances responded less strongly. We find that the learning is also stronger from the destinations with higher shares of Hispanic population and Mexican descent, but the effects do not differ substantially by other observable destination characteristics.

6. Conclusion

People are social entities who learn about information and form beliefs through their social connections. Among various sources of information, friends and family can be especially important when forming beliefs, particularly when there is considerable uncertainty and the stakes are high. In the context of the early-2020 Covid-19 pandemic, we study the effects of migrants' exposure to U.S. social distancing practices on social distancing behavior in Mexico.

Using detailed *municipio*-to-county migrant network data and observed social distancing behavior in U.S. counties based on smartphone tracking data, we construct the exposure to U.S. social distancing for the residents of each Mexican *municipio*. We find that this exposure had a positive impact on the Mexican residents' social distancing behavior, and that this effect was likely driven by learning, rather than assortative matching between origin places and destination places, the possibility of disease transmission along the network, or changing remittance transfers. Mexican regions with more favorable socio-economic conditions responded more strongly to U.S. social distancing exposure, and the effects are stronger when a *municipio* is connected with destinations with a higher Hispanic population share.

To get a sense for the potential public health impacts of increased social distancing in Mexico, we draw on the analysis of Glaeser et al. (2020), who find that a ten percentage point decrease in mobility leads to a 25–30 percent reduction in Covid-19 cases per capita. Our supplementary estimates using Facebook data in Table B7 imply that the mean increase in U.S. social distancing of 13 percent (Table 2) increased Mexican social distancing by 4.0 to 4.9 percent on average. In turn, the Glaeser et al. (2020) estimates imply a substantial 9.9 to 14.7 percent reduction in Covid-19 cases per capita in Mexico. This back-of-the-envelope calculation suggests that social learning likely generated important public health benefits.

Together, these findings highlight the importance of social networks in influencing individuals' compliance with or rejection of public health recommendations in the context of an emerging pandemic. We chose to examine this kind of social

[41] The first two interaction term coefficients in Table 6 are statistically significant at the 1 percent level when implementing a Bonferroni correction for multiple testing across the 6 specifications.

learning in the international context because it resolves difficult identification issues that arise in other contexts, since events in Mexico were unlikely to have a significant influence on U.S. social distancing behaviors or policies. However, our conclusions are nonetheless informative regarding the broader importance of personal connections when policy makers seek to change fundamental social behaviors, such as social distancing or wearing masks during a disease outbreak.

Declaration of Competing Interest

None.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jebo.2021.12.028.

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