When Interdependence Backfires: The Coronavirus Infected Three Times More People in Rice-Farming Areas During Chinese New Year

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Abstract

Interdependent cultures around the world have generally controlled COVID-19 better. We tested this pattern in China based on the rice theory, which argues that historically rice-farming regions of China are more interdependent than wheat-farming areas. Unlike earlier findings, rice-farming areas suffered more COVID-19 cases in the early days of the outbreak. We suspected this happened because the outbreak fell on Chinese New Year, and people in rice areas felt more pressure to visit family and friends. We found historical evidence that people in rice areas visit more family and friends for Chinese New Year than people in wheat areas. In 2020, rice areas also saw more New Year travel. Regional differences in social visits were correlated with COVID-19 spread. These results reveal an exception to the general idea that interdependent culture helps cultures contain COVID-19. When relational duties conflict with public health, interdependence can lead to more spread of disease.

Keywords

COVID-19, rice theory, culture, collectivism, interdependence

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COVID-19 Spread More During Chinese New Year in Rice-Farming Areas of China Than Wheat-Farming Areas Because of Stronger Relationship Ties

Research on the COVID-19 pandemic has found that culture matters. Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has infected and killed fewer people in cultures that are collectivistic, with tight social norms and less-mobile relationships (English et al., 2022; Gelfand et al., 2021; Lu et al., 2021; Salvador et al., 2020). In contrast, individualistic cultures like the United States and United Kingdom have had some of the worst COVID-19 outcomes so far. Despite this general trend, we argue that the relational ties of interdependent cultures can worsen COVID-19 under particular circumstances. One circumstance is when relational duties conflict with COVID precautions.

To test this idea, we took advantage of the happenstance of when COVID-19 first broke out in China. The Chinese government locked down Wuhan on January 23, 2020, which just so happened to be the day before Chinese New Year (also called "Spring Festival" and the Chinese "Lunar New Year"). Despite the lockdown, the virus had already escaped. And after it escaped, it did not spread evenly. We found that COVID-19 spread more in historically rice-farming prefectures of China than in wheat-farming prefectures during Chinese New Year 2020. Why did the general pattern of strong COVID performance in interdependence fail in this context?

One possibility is that Wuhan is closer to rice areas than it is to wheat areas, and rice areas suffered more cases because of proximity to the epicenter. Yet it just so happens that

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Wuhan is located on a horizontal line that divides China into the mostly wheat-farming north and mostly rice-farming south. Thus, distance cannot explain the pattern.

Another possibility is that Chinese New Year influenced the spread of the virus. The coronavirus spreads primarily through social interaction, and culture influences social contact (Salvador et al., 2020). We know from previous studies that rice-farming areas in China are more interdependent than wheat-farming areas (Talhelm & English, 2020; Talhelm et al., 2014). If we look at cases over the long run, interdependent rice-farming areas have outperformed wheat areas in COVID control. China's rice areas have suffered fewer COVID-19 cases than the more independent wheat-farming areas, as was the case around the world (Talhelm et al., 2022).

Yet that is over the long term. That study analyzed cases from April 2020 to February 2021. In this study, we argue that Chinese New Year 2020 was a special time. Our reasoning is that the interdependent culture of rice areas made it *more* likely that they would see family and friends during Chinese New Year. In this way, the tight social ties of rice-farming cultures ended up spreading the virus more during this holiday.

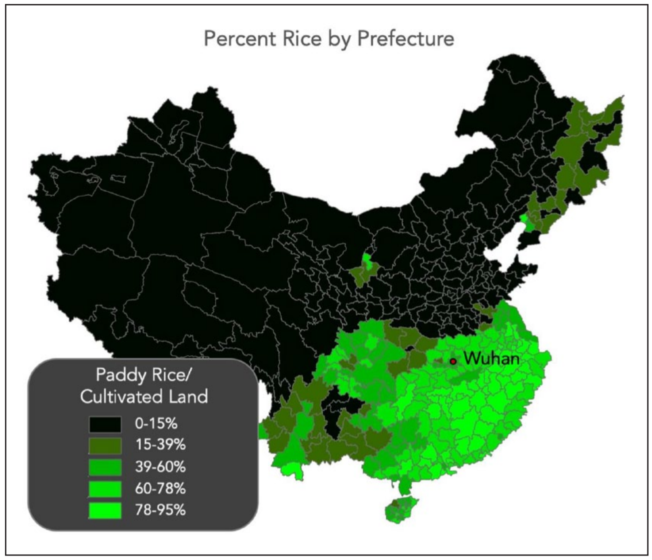

Figure 1. Percentage Rice by Prefecture in China.
Note. This map shows the percentage of cultivated land devoted to paddy rice per prefecture. Rice farming is most common near the Yangtze River in the middle of China and further south. Wuhan was the epicenter of the outbreak. Wuhan happens to be near the rice–wheat dividing line, which meant the virus could easily spread to both rice and wheat areas. Although this map uses modern rice statistics, analyses have found that these modern data are correlated highly with data from 1914 and even with the distribution of archeological rice artifacts dating back thousands of years (Talhelm & English, 2020).

The Rice Theory

The rice theory argues that traditional rice farming made rice cultures more interdependent than areas that farmed wheat and other dryland crops like barley, corn, and potatoes (Talhelm et al., 2014; Talhelm & Oishi, 2018). The rice plant has two major differences from crops like wheat.

First, rice farming involved more work than wheat. Paddy rice farming requires about twice the labor per hectare of wheat and other major dryland crops (Talhelm & Oishi, 2018). In response, rice farmers developed labor-sharing customs that reinforced interdependence.

Second, rice grows best in standing water. Rice villages built irrigation systems to control water levels in their fields. Those systems required farmers to coordinate decisions like when to flood their fields and how to divide labor for building and repairing the channels. In contrast, most wheat farming relied on rain, which falls regardless of whether farmers cooperate with each other.

If true, the rice theory means that Han China has two separate cultures—a more individualistic wheat culture in the north and a more interdependent rice culture in the south (Figure 1). In line with this idea, studies have found that people in southern China show more hallmarks of interdependent culture, such as in their self-concept, loyalty/nepotism toward close friends, and tight social norms (Dong et al., 2018; English et al., 2022; Talhelm & English, 2020; Talhelm et al., 2014).

Rice Cultures Encourage Social Interaction

There are some hints in prior research at the idea that rice culture encourages social interaction, which spreads COVID-19. For example, researchers found that people sitting in Starbucks in rice areas such as Hong Kong and Shanghai were more likely to be sitting with other people (Talhelm et al., 2018). On weekdays, roughly 25% of people in rice-farming cities were sitting alone, whereas 35% of people in wheat-farming cities were sitting alone.

Other research hints at the importance of family ties in rice areas. In pre-modern rice farming, Chinese farmers strongly preferred to exchange labor within the family, rather than outside the family or through hired labor (Fei, 1945, p. 65). Rice areas in China have more records of family clans than wheat areas (Noblit, 2022). In modern China, rice areas have more durable marriages (lower divorce rates), even after accounting for economic development (Talhelm et al., 2014).

In contrast, research has linked wheat farming to looser family ties. For example, a study found that countries that farm wheat rate family as less important in life (Ang & Fredriksson, 2017). That study also found that people in wheat cultures are less likely to agree that children must always love and respect their parents. This holds true even when comparing nations within Europe or regions within the United States.

Family ties are important for COVID-19 because the initial outbreak coincided with Chinese New Year. Chinese New Year is traditionally an important time for friends and family to get together. Because of the cultural value placed on relationships, people in rice areas may have felt more pressure to visit family and friends for Chinese New Year. This idea is consistent with the finding that people in rice areas of China perceive tighter social norms than people in wheat areas (Talhelm & English, 2020).

These new year gatherings are plausible spreaders of COVID-19. An early epidemiology study in China found that interactions in the household and community were major sources of early infections (Lauerman, 2020). If people in rice-farming regions met with more relatives and close friends than people in wheat-farming areas, they could have spread the coronavirus more over Chinese New Year. To test this idea, we analyzed the number of confirmed COVID-19 cases in different regions of China during Chinese New Year 2020.

Low Relational Mobility Helps Contain COVID, Except During Chinese New Year

Relational mobility is another possible contributing factor. A study of 39 societies around the world found that cultures with a history of rice farming have lower relational mobility (Thomson et al., 2018). In cultures with low relational mobility (such as Japan), relationships tend to be more binding and more stable over time. People report feeling less freedom to leave unsatisfying relationships, meeting fewer new acquaintances in the last month, and having fewer romantic partners throughout their lifetime (Schug et al., 2010; Thomson et al., 2018). This low mobility fits with the social ecology of rice farming, which enmeshed farmers with tight, binding labor-sharing relationships and shared irrigation networks (Talhelm & Oishi, 2018).

Rice cultures tend to have low relational mobility, and that low relational mobility helps explain why rice cultures suffered fewer COVID-19 cases (Talhelm et al., 2022). Meeting fewer new people and having fixed relationship networks should limit the spread of COVID-19. However, in this study, we suggest that Chinese New Year 2020 was an exceptional situation. It was a time when the long-term ties of low-mobility rice areas made it harder to refuse to visit family and friends and thus harder to avoid COVID-19.

High relational mobility is usually connected to more COVID-19, but there is some evidence that high relational mobility can sometimes be helpful in preventing infections. The idea is that high relational mobility is not a *permanent* state of high social contact. Instead, relational mobility is more in line with what cultural psychologists defined it to be—the *freedom and choice* to enter and exit relationships (Schug et al., 2010; Thomson et al., 2018).

During the COVID-19 outbreak in 2020, researchers tracked people's movement using cell phone data from 33 countries around the world (Freeman & Schug, 2021). When COVID-19 started to spread in each country, people in high-mobility cultures cut their movement *more* than people in low-mobility cultures. In other words, the relationship freedom of high-mobility cultures seems to have made it easier for them to cut their mobility. Freeman and Schug (2021) explained this by saying that people from societies with high relational mobility, "may have had greater control over their social connections and were thus better able to decrease their geographic mobility" (p. 7).

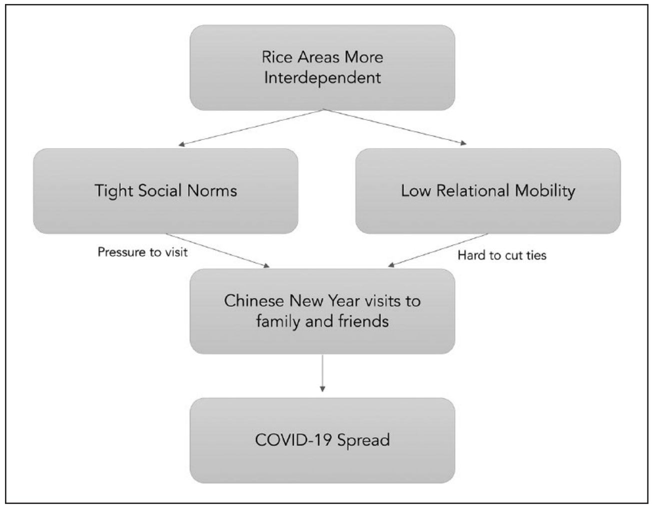

Figure 2. Conceptual Model Linking Culture to COVID-19 Outcomes During Chinese New Year.
Note. This model illustrates the documented link of interdependent rice cultures with tight social norms (Talhelm & English, 2020) and low relational mobility (Thomson et al., 2018). We then extend these to the increased visits to family and friends in rice areas for Chinese New Year.

And on the flip side, the tight ties of low-mobility cultures make it harder to cut social interactions. Thus, people in low-mobility cultures may have had a harder time cutting ties during Chinese New Year. Figure 2 ties these cultural characteristics of rice areas together, from tight norms and low mobility to COVID-19 spread during Chinese New Year.

Relationship Entry Versus Exit

Researchers have argued that relational mobility has an entry facet and an exit facet (Thomson et al., 2018). The entry facet is about opportunities to form new relationships. The exit facet is about the ability to remove oneself from relationships or groups. Theoretically, high entry might be more likely to spread cases between clusters, whereas low exit might be more likely to accelerate spread within clusters.

Our explanation of spread through social visits for Chinese New Year fits with the low exit facet idea. However, we do not have direct data on these two facets or how much spread was between clusters versus within clusters. Thus, the question of whether entry or exit was more important awaits further research.

Study 1: COVID-19 Spread More in Rice Areas

Method

Data Availability. The COVID-19 data, regional variables, analysis scripts, and statistical output are available on the Open Science Framework: https://osf.io/ms48g/?view_only=dd4f9fa5fad449668879e8337954a7e2. The China Family Panel Study data are available through Peking University. These studies were not pre-registered. Statistical power was determined by the geographic units available. With 317 prefectures, the sample size had over 99% statistical power to detect a medium effect size ($r = .3$).

COVID-19 Case Data. We gathered the number of confirmed COVID-19 cases per capita in each province and prefecture from the websites[1] of each province's ($N = 30$) and prefecture's ($N = 317$) health commission. Because Wuhan Prefecture in Hubei Province was the center of the outbreak, it could have an outsized influence on the results. Thus, we excluded data from Hubei from the province-level analysis, and we excluded Wuhan from the prefecture-level analysis. We also ran a model excluding data from all prefectures in Hubei Province as a robustness check.

Timeline. Supplemental Table S1 lists all variable sources and theoretical rationales. We analyzed data from the first day of Chinese New Year in 2020 (which coincided with the closure of Wuhan on January 23, 2020) to the end of Chinese New Year (February 3, 2020). Because there is a delay between being exposed and testing positive, we also ran analyses with an extra 7 days after Chinese New Year (February 10, 2020). An extra 7 days fits with viral incubation data from Hubei showing that over 99% of symptomatic cases could be identified within 7 days of exposure (Lauer et al., 2020).

Our theory is that COVID-19 spread more in rice areas in these early days because there were not yet strong norms about the importance of avoiding COVID. Therefore, we also tested for spread in Chinese New Year 2021 (January 31–February 6) and 2022 (February 11–17). By this point, norms for avoiding COVID were strong enough that they should overpower the norms of visiting family and friends over the holidays. If our explanation is correct, rice areas should no longer suffer more cases during Chinese New Year 2021 and 2022.

Rice Farming. To measure rice, we used the percentage of cultivated land devoted to paddy rice per prefecture and province (Talhelm et al., 2014). We used the earliest available data on the Bureau of Statistics website, from 1996. Although the Bureau's website only goes back to 1996, these data are strongly correlated with more limited data available from 1914 and from long-run environmental suitability data (Talhelm & English, 2020; Talhelm et al., 2014). In other words, data suggest that the 1996 statistics adequately represent historical rice farming. We sourced prefecture-level rice data from the earliest provincial statistical yearbook we could locate, which was 2002 for most provinces.

Travel From Wuhan. One important control variable is the amount of travel from Wuhan to each province. We collected data on the percentage of people who traveled out of Wuhan to other provinces from the Baidu Maps app, which estimated travel using people's smartphone location data (similar to Google Maps, Fang et al., 2020; https://qianxi.baidu.com/?city=420100). The estimates work like this. Imagine that, on 1 day, cell phone data show that 100 people traveled out from Wuhan. Twenty of those people went to Beijing. Thus, Beijing would get a value of 20%, meaning that 20% of the people who traveled out of Wuhan that day went to Beijing.

Because the virus's incubation period was most frequently between 3 and 7 days in 2020, we analyzed average mobility data for the week before the lockdown (January 16th to the 23rd). Because Wuhan is in the center of China, it is close to both rice and wheat provinces (Figure 1). That meant both rice and wheat provinces received roughly similar amounts of travel from Wuhan, as evidenced by the non-significant correlation between rice and travel from Wuhan $r(28) = .26$, $p = .169$.

By controlling for mobility, we are testing for a particular type of social interaction, rather than simply traveling for Chinese New Year. Thus, the analysis rules out differences in travel itself. This is a more conservative test of differences because rice culture could also encourage more travel during the Chinese New Year holiday. However, we analyze the more specific mechanism of social visits during the Chinese New Year holiday.

Distance to Wuhan. We also ran models controlling for distance to Wuhan, which is another measure of connection to Wuhan. We used this as a robustness check for the travel data. For example, if some areas have fewer people who use Baidu Maps, the travel estimates could be too low. The distance measure does not suffer from this limitation.

Economic Development and Urbanization. To measure economic development, we used 2018 gross domestic product (GDP) per capita from the *China Statistical Yearbook*. We also ran analyses with time-lagged GDP because there is evidence of a lag between economic growth and cultural change (Grossmann & Varnum, 2015). We ran analyses using 1996 GDP as a check for time lag (Supplemental Table S2).

To measure urbanization, we gathered statistics on provinces' percent of urban population from the *China Population and Employment Statistical Yearbook*. At the prefecture level, we used the city tier system, which ranks prefectures into the most urban, developed places in the first tier (such as

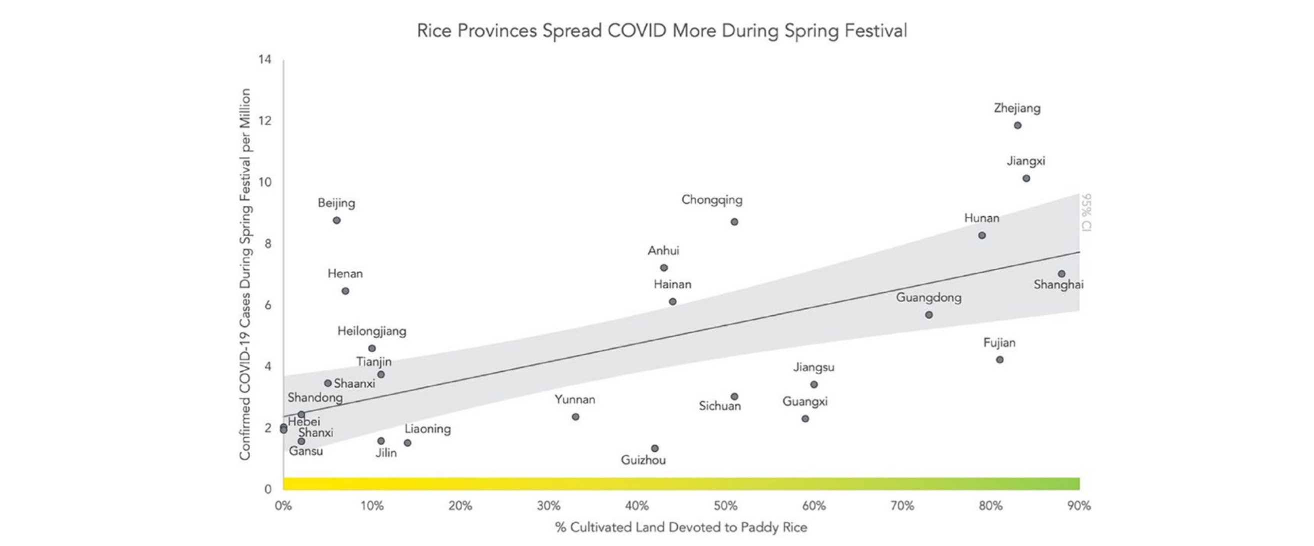

Figure 3. Rice-Farming Provinces Had More COVID-19 Cases During Chinese New Year.
Note. We measured COVID-19 cases from the closure of Wuhan (January 23, 2020) to the end of the Chinese New Year (February 3, 2020).

Beijing and Shanghai), second tier (such as Nanjing), and the least urban, least developed places in the third tier. We used the tier rankings of *Yicai Global*, which incorporate several variables, such as transportation, consumption, and commerce.

Testing Policies. One potential confound is if different areas test more than other areas. To account for this, we collected data on different provinces' COVID-19 testing policies. We located day-to-day data on provinces' testing policies (Oxford University, 2021). Researchers at Oxford coded policies from 0 to 3, where higher values represent broader testing. For example, 1 represents the policy of testing only people who show symptoms and meet specific criteria (such as health care workers). Three represents public testing available to all. We calculated provinces' average policies for the same dates as the COVID-19 case data (January 23 to February 3, 2020).

Pathogen Prevalence. We controlled for data on morbidity rates from 26 communicable disease to account for pathogen prevalence theory. This theory argues that environments with more communicable make cultures more xenophobic, collectivistic, and prepared to fend off disease (Fincher et al., 2008).

Statistical Analysis. For the province data, we ran simple regression models using rice to predict COVID-19 cases. For the prefecture data, we ran hierarchical linear models with prefectures nested in provinces using the LMER function in the program R. These models take into account the fact that prefectures in the same province are not truly independent observations.

Results

Province-Level Analysis. Rice-farming provinces suffered more COVID-19 cases during Chinese New Year (Table 1, Model 1, Figure 3). Rice continued to predict COVID-19 cases after controlling for potential confounds. Rice remained significant after accounting for the percentage of people traveling from Wuhan (Table 1, Model 2), urbanization (Model 3), GDP per capita (Model 4), pathogen prevalence (Model 5), distance from Wuhan (Model 6), and the prevalence of COVID testing (Model 7).

Not surprisingly, provinces received more travelers from Wuhan had more cases (p = .028, Model 2). Urbanized provinces suffered more cases, even after controlling for GDP (Model 6). GDP, pathogen prevalence, and distance from Wuhan were not significant.

Prefecture-Level Analysis. Zooming into the prefecture level gives more fine-grained detail on regional differences. In hierarchical linear models with prefectures nested in provinces, rice-farming prefectures had more COVID-19 cases (Table 2, Model 1). To give a sense of the size of the differences, we categorized prefectures into rice (≥50% cultivated land devoted to paddy rice) and wheat (<50%). In raw numbers, rice prefectures had 16.86 cases per million people (SD = 46.61), whereas wheat prefectures had 4.95 cases per million (SD = 15.45, t[146.46] = −2.79, p = .006, d = −0.46, 95% CI = [−0.204, −0.035]). In other words, rice prefectures suffered three times more COVID-19 cases per capita than wheat prefectures (Figure 4).

Similar to the province analysis, the effect remained significant after we accounted for the percentage of people traveling from Wuhan (Table 2, Model 2), urbanization (Table 2,

Table 1. Provinces' History of Rice Farming Predicts COVID-19 Cases During Chinese New Year 2020.

	B	*SE*	*t*	*p*	95% CI	R^2
Model 1						
Paddy rice, %	0.06	0.01	4.16	<.001	[0.030, 0.088]	.36
Model 2						
Paddy rice, %	0.05	0.01	3.74	<.001	[0.023, 0.079]	.45
Travel from Wuhan	0.01	0.00	2.32	.028	[0.001, 0.016]	
Model 3						
Paddy rice, %	0.05	0.01	2.65	.001	[0.020, 0.071]	.55
Travel from Wuhan	0.01	0.00	5.62	.007	[0.003, 0.016]	
Urban, %	0.08	0.03	−0.35	.014	[0.018, 0.146]	
Model 4						
Paddy rice, %	0.04	0.01	3.15	.004	[0.015, 0.072]	.53
Travel from Wuhan	0.01	0.00	2.84	.009	[0.003, 0.017]	
Urban, %	0.07	0.05	1.41	.170	[−0.031, 0.167]	
GDP per capita	0.01	0.02	0.38	.707	[−0.027, 0.040]	
Model 5						
Paddy rice, %	0.05	0.01	3.45	.002	[0.018, 0.072]	.58
Travel from Wuhan	0.01	0.00	3.60	.001	[0.005, 0.020]	
Urban, %	0.11	0.05	2.20	.038	[0.007, 0.213]	
GDP per capita	−0.00	0.02	−0.29	.771	[−0.039, 0.029]	
Pathogen prevalence	0.00	0.00	2.02	.055	[−0.000, 0.005]	
Model 6						
Paddy rice, %	0.04	0.01	2.89	.009	[0.012, 0.071]	.57
Travel from Wuhan	0.01	0.01	2.19	.040	[0.001, 0.020]	
Urban, %	0.12	0.05	2.28	.033	[0.011, 0.224]	
GDP per capita	0.00	0.01	−0.30	.769	[−0.039, 0.030]	
Pathogen prevalence	0.00	0.00	1.97	.062	[−0.000, 0.005]	
Road distance from Wuhan	−0.15	0.13	−1.10	.284	[–0.422, 0.130]	
Road distance from Wuhan^2	0.01	0.01	1.07	.297	[−0.009, 0.030]	
Model 7						
Paddy rice, %	0.04	0.01	2.89	.009	[0.012, 0.073]	.61
Travel from Wuhan	0.01	0.01	2.19	.040	[0.001, 0.020]	
Urban, %	0.12	0.05	2.24	.036	[0.009, 0.225]	
GDP per capita	0.00	0.02	−0.22	.830	[−0.039, 0.032]	
Pathogen prevalence	0.00	0.00	1.94	.066	[−0.000, 0.005]	
Road distance from Wuhan	−0.17	0.14	−1.21	.239	[−0.465, 0.122]	
Road distance from Wuhan^2	0.01	0.01	1.19	.249	[−0.009, 0.033]	
COVID testing policy[a]	−0.01	0.01	−0.61	.552	[−0.023, 0.013]	

Note. These analyses use the raw number of cases per 10,000 because data skewness (0.86) and kurtosis (−0.16) were under the recommended limits (Curran et al., 1996). Supplemental Table S1 lists all variable sources and theoretical rationales. Urbanization is the percentage of urban residents per province in 2018 from *China Population and Employment Statistical Yearbook*. GDP data are log RMB from 2018. Pathogen prevalence is the average morbidity rates for human-transmitted diseases from the 2001 *China Statistical Yearbook of Health*. Road distance from Wuhan is the distance (in 1,000 km log) from the provincial capital to Wuhan. Prefecture analyses (Table 2) found that both distance and distance squared were significant. CI = confidence interval; GDP = Gross domestic product.

[a]Testing policy is the average of three categories of testing from 0 (least testing) to 3 (public testing open to all) averaged over the dates in our analysis (January 23 to February 3, 2020).

Model 3), GDP per capita (Table 2, Model 4), pathogen prevalence (Table 2, Model 5), and road distance from Wuhan (Table 2, Model 6). Similar to the province analysis, COVID-19 cases were higher in places with more travel from Wuhan and more urbanized prefectures. Unlike the province analyses, distance from Wuhan was significant. This could be because prefectures provide a larger sample size and more granularity than provinces. Similar to the province analysis, GDP and pathogen prevalence did not predict COVID-19 cases.

Robustness Checks. We ran a series of robustness checks to test whether the results were reliable to different specifications (Table 3). Rice remained significant after excluding all prefectures in Hubei Provinces (Model 1), excluding outlying

Table 2. Prefectures' History of Rice Farming Predicts COVID-19 Cases During Chinese New Year.

	B/γ	*SE*	*t*	*p*	95% CI	R^2
Model 1						
Prefecture paddy rice, %	0.11	0.04	2.99	.003	[0.037, 0.178]	.81
Model 2						
Prefecture paddy rice, %	0.11	0.02	5.20	<.001	[0.071, 0.154]	.83
Travel from Wuhan	0.01	0.00	25.04	<.001	[0.014, 0.016]	
Model 3						
Prefecture paddy rice, %	0.10	0.01	4.70	<.001	[0.061, 0.145]	.84
Travel from Wuhan	0.02	0.00	24.41	<.001	[0.014, 0.016]	
Urbanization (City Tier)	0.06	0.03	4.25	<.001	[0.030, 0.082]	
Model 4						
Prefecture paddy rice, %	0.10	0.02	4.50	<.001	[0.058, 0.144]	.84
Travel from Wuhan	0.02	0.00	24.34	<.001	[0.014, 0.016]	
Urbanization (City Tier)	0.05	0.02	3.31	.001	[0.021, 0.084]	
GDP per capita	0.01	0.01	0.36	.718	[−0.022, 0.033]	
Model 5						
Prefecture paddy rice, %	0.10	0.02	4.48	<.001	[0.058, 0.144]	.84
Travel from Wuhan	0.02	0.00	23.74	<.001	[0.014, 0.016]	
Urbanization (city tier)	0.05	0.02	3.36	<.001	[0.022, 0.085]	
GDP per capita	0.01	0.01	0.35	.727	[−0.022, 0.033]	
Pathogen prevalence	−0.00	0.00	−0.82	.421	[−0.007, 0.003]	
Model 6						
Prefecture paddy rice, %	0.07	0.02	3.20	.003	[0.028, 0.104]	.85
Travel from Wuhan	0.01	0.00	17.92	<.001	[0.011, 0.013]	
Urbanization (city tier)	0.05	0.02	3.53	<.001	[0.024, 0.083]	
GDP per capita	0.01	0.01	0.49	.622	[−0.019, 0.032]	
Pathogen prevalence	−0.00	0.00	−0.15	.885	[−0.004, 0.004]	
Road distance from Wuhan	−0.55	0.13	−4.28	<.001	[−0.821, −0.314]	
Road distance from Wuhan^2	0.04	0.01	3.82	<.001	[0.019, 0.056]	
Model 7						
Prefecture paddy rice, %	0.07	0.02	3.13	.003	[0.028, 0.104]	.85
Travel from Wuhan	0.01	0.00	17.13	<.001	[0.012, 0.013]	
Urbanization (city tier)	0.05	0.02	3.52	<.001	[0.024, 0.084]	
GDP per capita	0.01	0.01	0.49	.626	[−0.019, 0.032]	
Pathogen prevalence	−0.00	0.00	−0.14	.889	[−0.004, 0.004]	
Road distance from Wuhan	−0.54	0.13	−4.23	<.001	[−0.821, −0.314]	
Road distance from Wuhan^2	0.04	0.01	3.78	<.001	[0.019, 0.056]	
COVID testing policy[a]	0.00	0.02	0.02	0.983	[−0.027, 0.029]	

Note. All analyses are hierarchical linear models with prefectures nested in provinces. γ represents prefecture-level and province-level regression coefficients. Prefecture analyses used the square root of cases per 10,000 because the raw number of cases exceeds the cutoffs for skewness (6.23) and kurtosis (43.50; Curran et al., 1996). Urbanization uses city tier classifications, recoded such that larger numbers represent more urbanized places. GDP data are log RMB from 2019. Pathogen prevalence is the average morbidity rates for human-transmitted diseases from the 2001 *China Statistical Yearbook of Health*. Road distance from Wuhan is in 1,000 km, log transformed. R^2 is the *R* squared conditional, which includes fixed and random effects. CI = confidence interval.

[a]Testing policy is the average of three categories of testing from 0 (least testing) to 3 (public testing open to all) averaged over the dates in our analysis (January 23 to February 3, 2020).

provinces (Model 2), expanding the COVID-19 case count window to a week after Chinese New Year (Model 3), and using time-lagged GDP per capita (Model 4). In the Supplemental Materials, we present additional tests of general Chinese New Year travel, population size, median age, population density, regional history of SARS cases, and more COVID-19 policy measures (Supplemental Tables S5 and S6).

COVID-19 Spread Was Lower in Rice Areas After Chinese New Year. Our theory is that rice areas had more COVID-19 cases because of the social expectations around Chinese New Year. Our explanation would be contradicted if rice areas had more COVID-19 cases over the long term. To test this idea, we compared our Chinese New Year data to a published comparison of COVID-19 cases across China after Chinese New

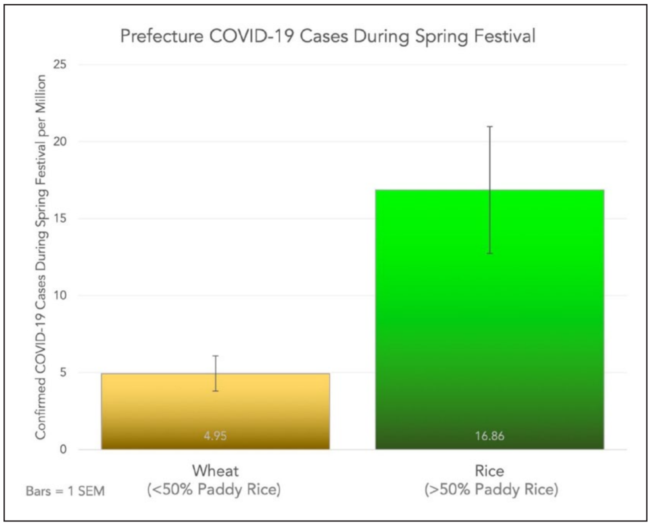

Figure 4. Rice-Farming Prefectures Had More COVID-19 Cases During Chinese New Year.
Note. Prefectures with a history of rice farming had more COVID-19 cases than wheat-farming prefectures during Chinese New Year, January 23, 2020 to February 3, 2020. This analysis bins prefectures into rice (>50% farmland devoted to rice) and wheat (<50% farmland devoted to rice), but the main analyses use the full continuous rice variable.

Year 2020 up to the start of Chinese New Year 2021 (from April 8, 2020 to February 12, 2021; Talhelm et al., 2022).

The data from after Chinese New Year showed the opposite pattern. Rice-farming prefectures outperformed wheat-farming areas after Chinese New Year (Figure 5). These longer-term data are consistent with the general finding that COVID-19 control is stronger in cultures that are more interdependent, with low relational mobility and tight social norms (Gelfand et al., 2021; Kumar, 2021; Salvador et al., 2020).

In the case of China, one alternative explanation is that rice-farming areas had fewer cases after Chinese New Year because the earlier infections built up more immunity in the population. However, that seems unlikely. Most of the population was still uninfected by the end of Chinese New Year. Even if the real infection rate was 100 times higher than the Chinese New Year numbers, that would still leave over 99% of the population vulnerable to infection. Thus, the later outperformance in rice areas is more consistent with cultural explanations than a buildup of immunity from Chinese New Year.

We also analyzed Chinese New Year cases in 2021 and 2022 (Figure 6). If our explanation for the rice–wheat differences is correct, rice areas of China should *not* experience more COVID-19 cases than wheat areas during the Chinese New Year holidays in 2021 and 2022. That is because strong norms to fight COVID-19 were established by Chinese New Year 2021.

Unlike in 2020 ($r = .62$, $p < .001$), there was no significant correlation between rice and cases per million during Chinese New Year in 2021 ($r = .22$, $p = .244$) or 2022 ($r = .08$, $p = .684$). This fits with the explanation that the surge in cases during Chinese New Year was partly a product of unclear norms about COVID-19. Once the threat of the virus was more clearly established and social norms solidified in 2020, these strong norms likely took precedence over the norms for visiting family and friends during Chinese New Year.

Study 2: People in Rice Areas Visit More Family and Friends for Chinese New Year

Study 1 found that COVID-19 spread more in historically rice-farming areas of China during Chinese New Year 2020. We believe one possible explanation is the social obligation to visit family and friends during the holiday. In Study 2, we test whether there are cultural differences between rice and wheat areas in social visits for Chinese New Year.

Method

Visiting Family and Friends. We analyzed data from China Family Panel Study, a nationally representative survey of 11,697 people across 25 provinces. The survey asked two questions about visiting people for Chinese New Year:

> Research Question 1 (RQ1): "How many relatives' households visited your house during Chinese New Year this year?"
> Research Question 2 (RQ2): "How many of households of friends came to visit you during Chinese New Year this year?"

Note that the question asks how many *households* of relatives, rather than individual people. The survey defined relatives as people outside the nuclear family. Thus, children visiting their parents would not count, but visiting aunts, uncles, or cousins would count.

We added up these two numbers to get the total number of households visited. We square-root transformed the data because it was over the recommended cutoffs for skewness (4.27, cutoff = 2) and kurtosis (36.22, cutoff = 7; Curran et al., 1996). The sample size of 11,697 people is the number of respondents who had valid data for all of the variables in Table 4, Model 1.

The survey data are large scale and nationally representative, but a downside of this rare dataset is that it is only available for 2010. We believe the 2010 data reveal an enduring rice–wheat cultural difference in social visits for Chinese New Year, but we lack direct visiting data for 2020. Even if Chinese New Year visiting went up or down over time, our inference is still valid as long as *relative* regional differences persisted.

To make up for this shortcoming in the data, we analyzed cell phone travel data during Chinese New Year in 2019 and

Table 3. Rice-Farming Prefectures Had More COVID-19 Cases During Chinese New Year: Robustness Checks.

	B/γ	*SE*	*t*	*P*	95% CI	R^2
Model 1						
Robustness check: Excluding Hubei						
Paddy rice, %	0.05	0.02	2.35	.023	[0.012, 0.088]	.41
Distance from Wuhan	−0.60	0.21	−2.90	.004	[−1.086, −0.234]	
Distance from Wuhan^2	0.04	0.02	2.64	.009	[0.013, 0.074]	
Travel from Wuhan	0.01	0.01	1.26	.223	[−0.004, 0.021]	
Urbanization (city tier)	0.05	0.01	3.47	.001	[0.021, 0.075]	
GDP per capita	0.02	0.01	1.55	.122	[−0.005, 0.042]	
Pathogen prevalence	−0.00	0.00	−0.19	.849	[−0.005, 0.004]	
Model 2						
Robustness check: Excluding non-Han provinces						
Paddy rice, %	0.07	0.02	3.16	.003	[0.029, 0.106]	.85
Distance from Wuhan	−0.59	0.13	−4.40	<.001	[−0.882, −0.349]	
Distance from Wuhan^2	0.04	0.01	3.96	<.001	[0.022, 0.061]	
Travel from Wuhan	0.01	0.00	17.58	<.001	[0.011, 0.013]	
Urbanization (city tier)	0.06	0.02	3.56	<.001	[0.025, 0.087]	
GDP per capita	0.00	0.00	0.31	.758	[−0.022, 0.032]	
Pathogen Prevalence	−0.00	0.00	−0.01	.996	[−0.004, 0.004]	
Model 3						
Robustness check: Chinese New Year plus 1 week						
Paddy rice, %	0.06	0.03	2.20	.034	[0.013, 0.118]	.85
Distance from Wuhan	−1.10	0.18	−6.18	<.001	[−1.479, −0.781]	
Distance from Wuhan^2	0.08	0.01	5.72	<.001	[0.052, 0.104]	
Travel from Wuhan	0.02	0.00	16.19	<.001	[0.014, 0.017]	
Urbanization (city tier)	0.07	0.02	3.48	<.001	[0.032, 0.115]	
GDP per capita	0.00	0.02	0.07	.945	[−0.035, 0.036]	
Pathogen prevalence	−0.00	0.00	−0.29	.777	[−0.007, 0.005]	
COVID testing policy[a]	0.00	0.02	0.09	0.926	[−0.038, 0.042]	
Model 4						
Robustness check: Time-lagged GDP						
Paddy rice, %	0.07	0.02	3.32	.002	[0.030, 0.104]	.85
Distance from Wuhan	−0.54	0.13	−4.24	<.001	[−0.815, −0.308]	
Distance from Wuhan^2	0.04	0.01	3.77	<.001	[0.018, 0.056]	
Travel from Wuhan	0.01	0.00	18.04	<.001	[0.011, 0.013]	
Urbanization (city tier)	0.05	0.01	3.63	<.001	[0.023, 0.080]	
GDP per capita	0.01	0.01	0.89	.374	[−0.011, 0.030]	
Pathogen prevalence	−0.00	0.00	−0.02	.984	[−0.004, 0.004]	

Note. These analyses are hierarchical linear models with prefectures nested in provinces. γ represents province-level regression coefficients. Supplemental Table S1 lists all variable sources and theoretical rationales. These models present robustness checks to the prefecture analysis. Model 1 excludes all prefectures in Hubei Province. Model 2 excludes provinces with major non-ethnic-Han populations. Model 3 adds 7 days after the end of Chinese New Year to account for the incubation period. Model 4 tests time-lagged GDP from 2019 (log-transformed Yuan) because there is some evidence for a lag time between economic development and cultural change. Road distance from Wuhan is in 1,000 km, log transformed. R^2 is the *R* squared conditional, which includes fixed and random effects. [a]Testing policy is the average of three categories of testing from 0 (least testing) to 3 (public testing open to all) averaged over the dates in our analysis. This model tests Chinese New Year plus one week (January 23 to February 10, 2020). CI = confidence interval.

2020. This measures interprovince travel for Chinese New Year per capita. Although travel is not a direct measure of social visits, visiting family is the primary reason people travel for Chinese New Year (de Guzman, 2023).

Regional Difference Variables

Rice. We used the same rice data as in Study 1. We analyzed rice at the province level because the China Family Panel Study does not provide participant data at smaller geographic levels. However, the study does include codes for participants' county ($N = 162$ counties). This code does not tell us which county is which, but it does allow us to run hierarchical linear models that cluster participants in counties within provinces. This helps to statistically account for the fact that observations within the same county are not truly independent from each other.

Economic Development. We controlled for economic development because people in developed areas may be less likely to follow traditional customs. As in Study 1, we tested current GDP (year 2010) and time-lagged GDP (year 1996). Supplemental Table S2 finds that time-lagged GDP was a better predictor of visits than current GDP, which fits prior evidence of a lag time between economic development and cultural change (Grossmann & Varnum, 2015). Thus, the main analyses use time-lagged GDP.

Han Culture. We analyzed Census data on the percentage of ethnic Han people per province because other ethnic groups may have different cultural practices during Chinese New Year.

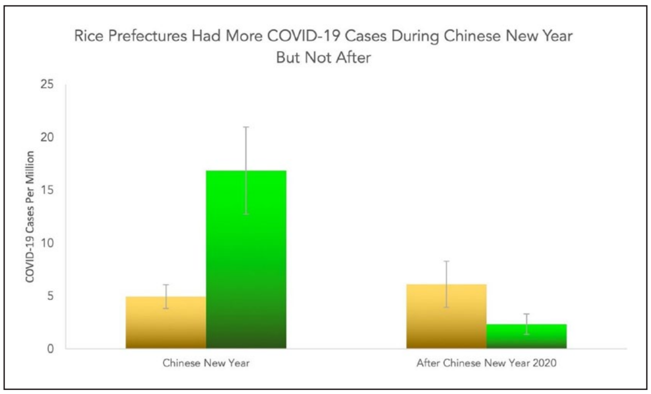

Figure 5. Higher COVID-19 Spread in Rice Areas Was Limited to Chinese New Year 2020.
Note. Chinese New Year cases (left) span January 23 to February 3, 2020. Cases after Chinese New Year (right) come from a published analysis of cases from April 8, 2020 to February 12, 2021 (Talhelm et al., 2022). February 12 was the first day of Chinese New Year 2021.

Family Characteristics

Income. We included several demographic variables for families. Participants reported yearly family net income in Yuan. We log-transformed income because it was over recommended cutoffs for skewness and kurtosis (Curran et al., 1996).

Education. Participants reported the highest education level in their household from 1 (*illiterate*) to 8 (*PhD*).

Urban. The survey includes a urban/rural variable set to 1 for families living in an urban area and 0 for families not in urban areas.

Family Size. Participants reported the size of their family. This family size data allows us to test one important possible mechanism for why rice areas had greater COVID transmission during Chinese New Year. We argue that the tight social ties of rice areas make people feel more pressure to see family and friends during Chinese New Year. However, an alternative explanation is that rice areas have bigger families on average (Gong et al., 2021). If so, they could visit more people simply because they have more family members. We test this mechanism by running an analysis controlling for family size.

Head of Household Characteristics. We controlled for several characteristics of the head of household: age, gender, employment, and marital status.

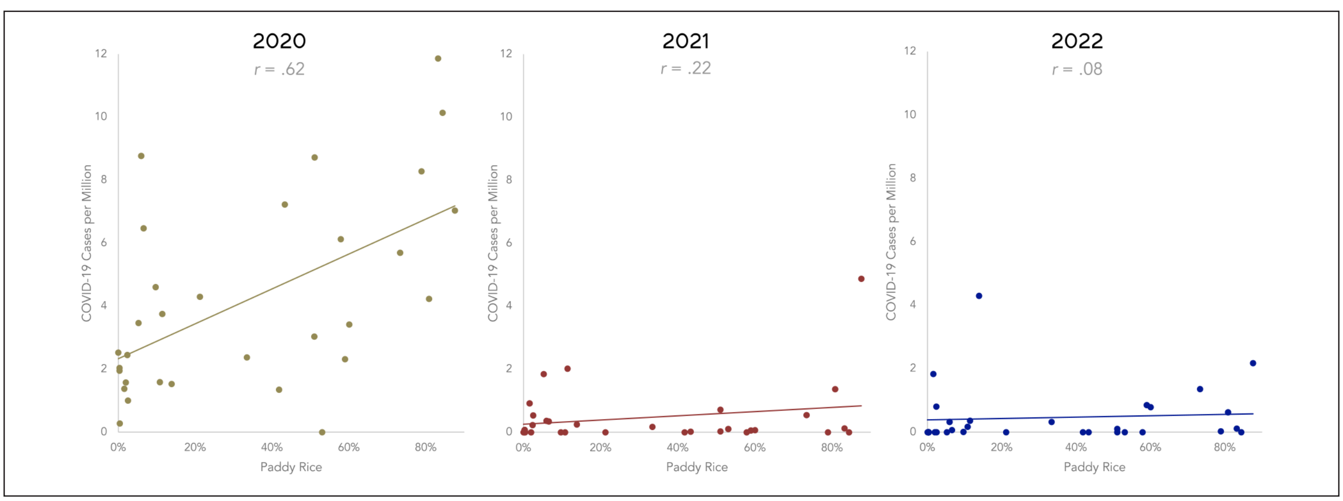

Figure 6. Rice Areas Had Significantly More Cases During Chinese New Year 2020, But Not 2021 or 2022.
Note. Rice areas had significantly more COVID-19 cases during Chinese New Year 2020 (left panel: $r = .62$, $p < .001$) but not in 2021 (middle panel: $r = .22$, $p = .244$) or 2022 (right panel: $r = .08$, $p = .684$). This fits with the explanation that rice-farming areas spread more COVID-19 cases during Chinese New Year 2020 because the long-standing norms to visit family and friends during the holiday were stronger than the norms to avoid COVID-19. But as COVID-19 norms strengthened, they overpowered norms to visit family and friends. Dots = provinces. Chinese New Year dates 2021: January 31 to February 6, 2022: February 11 to 17.

Table 4. People in Rice-Farming Provinces Visit More Family and Friends During Chinese New Year.

	B/γ	*SE*	*t*	*P*	95% *CI*	R^2
Model 1						
Family income	0.28	0.01	19.75	<.001	[0.25, 0.31]	.27
Education	0.03	0.01	2.73	.006	[0.01, 0.06]	
In urban area	−0.05	0.04	−1.44	.150	[−0.12, 0.02]	
GDP per capita	−0.13	0.03	−4.01	<.001	[−0.19, −0.07]	
Ethnic Han %	2.16	0.95	2.27	.035	[0.40, 3.92]	
Paddy rice %	0.79	0.35	2.29	.034	[0.15, 1.43]	
Model 2						
Controlling for family size						
Family income	0.24	0.01	17.34	<.001	[0.22, 0.27]	.27
Education	0.02	0.01	1.57	.116	[0.00, 0.04]	
In urban area	−0.01	0.03	−0.20	.844	[−0.07, 0.06]	
Family size	0.09	0.01	9.76	<.001	[0.07, 0.11]	
GDP per capita	−0.12	0.03	−3.77	.002	[−0.18, −0.06]	
Ethnic Han, %	2.21	0.95	2.34	.031	[0.46, 3.95]	
Paddy rice, %	0.73	0.34	2.13	.046	[0.10, 1.36]	
Model 3						
Including characteristics of head of household						
Family income	0.23	0.01	15.29	<.001	[0.20, 0.26]	.27
Education	0.02	0.01	1.75	.080	[0.00, 0.05]	
In urban area	0.00	0.04	0.12	.905	[−0.07, 0.07]	
Family size	0.08	0.01	8.42	<.001	[0.06, 0.10]	
Female	−0.17	0.03	−5.35	<.001	[−0.24, −0.11]	
Age	−0.02	0.01	−3.30	<.001	[−0.04, −0.01]	
Age^2	0.00	0.00	3.44	<.001	[0.00, 0.00]	
Divorced	−0.29	0.09	−3.36	<.001	[−0.46, −0.12]	
Single	−0.28	0.09	−3.21	.001	[−0.46, −0.11]	
Cohabiting	−0.70	0.22	−3.13	.002	[−1.14, −0.26]	
Widowed	−0.07	0.06	−1.13	.257	[−0.18, 0.05]	
Not employed	0.01	0.03	0.46	.644	[−0.05, 0.08]	
Other employment	−0.32	0.09	−3.67	<.001	[−0.49, −0.15]	
GDP per capita	−0.12	0.03	−3.62	.002	[−0.18, −0.06]	
Ethnic Han, %	2.15	0.95	2.25	.037	[0.39, 3.90]	
Paddy rice, %	0.74	0.35	2.15	.045	[0.10, 1.38]	
Model 4						
Excluding Anhui province						
Family income	0.22	0.01	14.94	<.001	[0.19, 0.25]	.23
Education	0.03	0.01	2.03	.043	[0.00, 0.05]	
In urban area	−0.03	0.04	−0.88	.380	[−0.10, 0.04]	
Family size	0.08	0.01	8.43	<.001	[0.06, 0.10]	
Female	−0.17	0.03	−5.28	<.001	[−0.24, −0.11]	
Age	−0.02	0.01	−3.09	.002	[−0.04, −0.01]	
Age^2	0.00	0.00	3.27	.001	[0.00, 0.00]	
Divorced	−0.30	0.09	−3.45	<.001	[−0.47, −0.13]	
Single	−0.28	0.09	−3.18	.001	[−0.46, −0.11]	
Cohabiting	−0.70	0.22	−3.12	.002	[−1.13, −0.26]	
Widowed	−0.07	0.06	−1.17	.242	[−0.18, 0.05]	
Not employed	0.01	0.03	0.42	.675	[−0.05, 0.08]	
Other employment	−0.33	0.09	−3.66	<.001	[−0.51, −0.16]	
GDP per capita	−0.10	0.02	−4.26	<.001	[−0.14, −0.06]	
Ethnic Han, %	1.56	0.71	2.20	.037	[0.24, 2.89]	
Paddy rice, %	0.60	0.25	2.37	.026	[0.13, 1.08]	
Provinces: 25, counties: 162, respondents: 11,697[a]						

Note. Models are hierarchical linear models with respondents nested in counties and provinces. γ = province-level coefficients. Family income is log Yuan. Urban: 0 = no, 1 = urban. Education: 1 (*illiterate*) to 8 (*PhD*). Married, employed respondents are reference groups. R^2 is conditional, including fixed and random effects. CI = confidence interval.

[a]Without head-of-household characteristics, the sample increases to 12,709. Model 4 excludes Anhui Province, leaving 11,486 respondents.

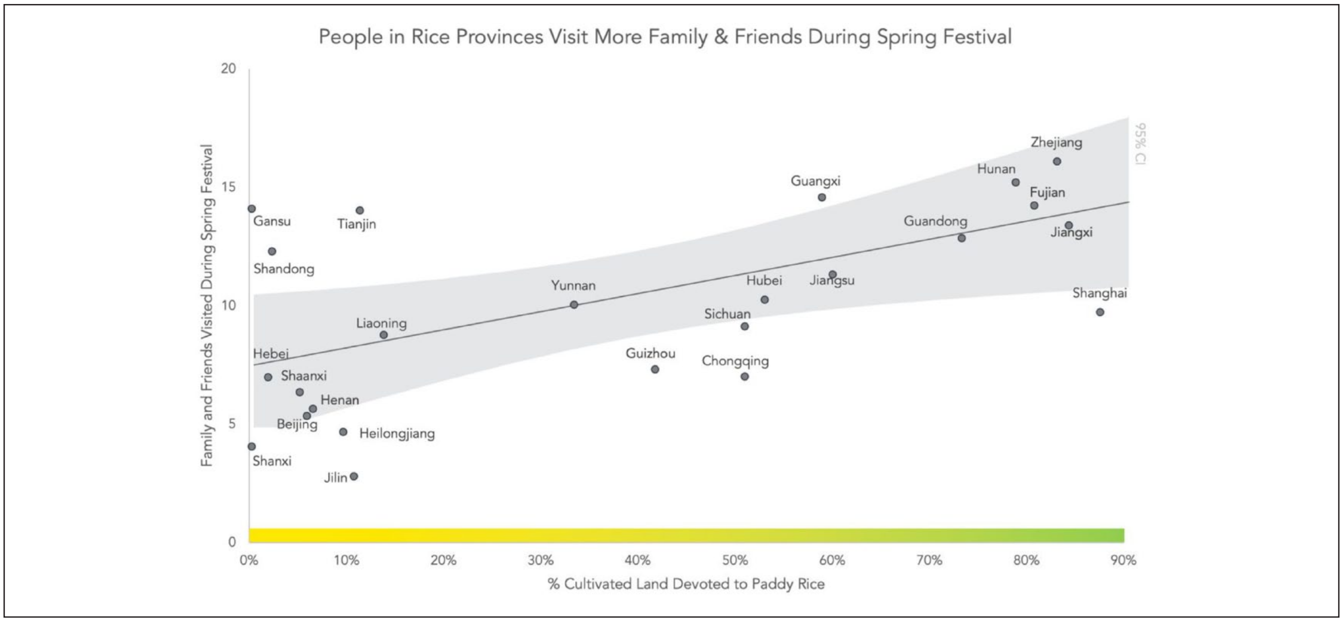

Figure 7. People in Rice-Farming Provinces Visit More Family and Friends During Chinese New Year.
Note. This graph shows the number of households of family and friends that visited the respondent household during Chinese New Year. The analyses use square-root transformed values to correct for skewness and kurtosis. The survey asked about the number of *households* that visited, rather than the number of individuals. This graph does not display Anhui Province, which was an outlier. Rice–wheat differences remained significant after excluding Anhui (Table 4).

Analysis. We ran hierarchical linear models with respondents nested in counties further nested in provinces. We used the LMER function in the program R. We discovered that Anhui Province was an outlier for social visiting. Although the overall average was visiting 8.75 households (SD = 10.94), Anhui Province averaged 25.16. The next highest province (Zhejiang) was 16.10. Thus, we ran an additional analysis excluding Anhui Province.

Results

People in rice areas visited more family and friends during Chinese New Year (Table 4, Model 1, Figure 7). This held even after controlling for characteristics of the head of household (Table 4, Model 3). Rice-wheat differences also persisted after excluding Anhui Province, which was an outlier in family visiting (Table 4, Model 4).

Rice Areas Experienced More Chinese New Year Travel in 2019 and 2020. Cell phone data revealed that rice areas experienced more travel in Chinese New Year in 2020 (r = .41, p = .023) and 2019 (r = .47, p = .009; Supplemental Table S4). This supports the idea that there are enduring rice-wheat differences in Chinese New Year practices, which persisted through 2020.

Do Bigger Families in Rice Areas Cause Differences in Social Visits? We argue that people in rice areas feel more social obligation to visit friends and family. However, another plausible mechanism is that people in rice-farming areas visited more households not because of social obligation, but simply because they have bigger families on average (Gong et al., 2021). We tested this by analyzing data on family size in the China Family Panel Study.

In line with prior findings, rice areas in the China Family Panel Study had larger families (γ = 0.75, p = .016, r = .27). This difference held after controlling for economic development, urbanization, education, and other confounds (Supplemental Table S2). In wheat provinces (<50% rice), the average family size was 3.5 people. In rice provinces (> 50%), the average family size was 3.9 people (Figure 8).

However, rice–wheat differences in social visits for Chinese New Year remained significant after controlling for family size (Table 4, Model 2). The regression coefficient for rice fell only slightly from 0.79 to 0.73 after accounting for family size. Thus, family size is not a strong explanation for rice-wheat differences in social visits.

Can Social Visits Account for Rice-Wheat Differences in COVID-19 Cases? Next, we asked whether it is mathematically plausible that the differences in social visits could account for the differences in coronavirus cases. On average, people in wheat provinces reported 8 household visits versus 10 households in rice provinces. Hypothetically, if visiting a household during this period caused an infection 2% of the time, visiting 8 households would accumulate a 15% risk of infection. That risk would rise to 18% after visiting 10 households.

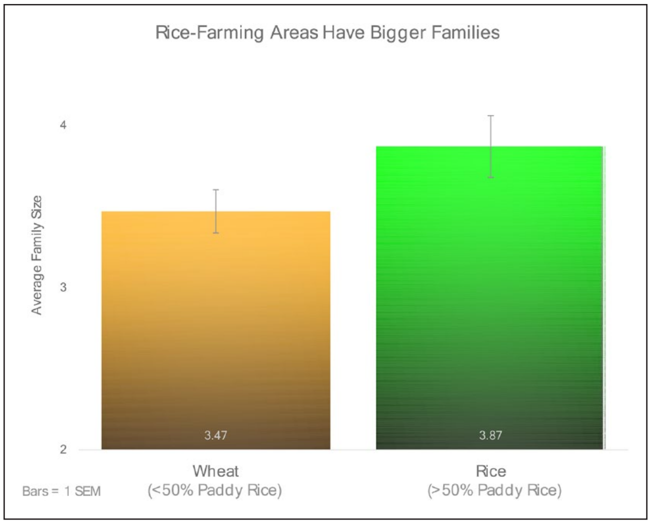

Figure 8. Rice–Wheat Differences in Family Size.
Note. In the 2010 China Family Panel Study, families were larger on average in rice provinces (right) than wheat provinces (left).

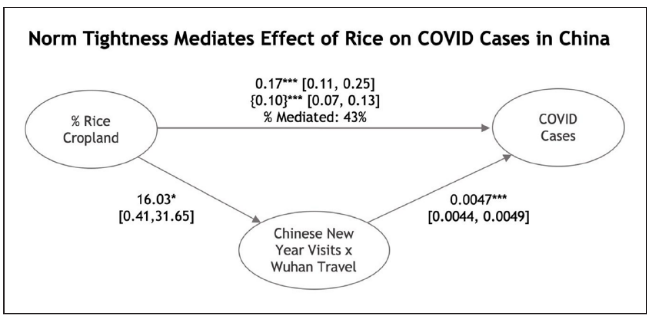

Figure 9. Chinese New Year Social Visits Partially Mediate Rice–Wheat Differences in COVID Cases.
Note. A mediation analysis found that social visits for Chinese New Year significantly mediated the effect of rice on COVID-19 cases ($B = 0.07$, 95% CI = [.03, 0.14], $p < .001$). The mediator is Chinese New Year social visits multiplied by provinces' travel from Wuhan. This interaction takes into account the fact that social visits were highly risky in regions that received travel from Wuhan and less risky in regions that did not receive travel from Wuhan. CI = confidence interval.

In other words, the rice–wheat difference in household visiting could have increased the relative risk of infection by 20%. If a portion of those infections then spread within the newly infected household, this could account for the infection rate that was three times higher in rice prefectures (16.9 infections per million) than wheat prefectures (5.0 per million, Figure 4). Although this calculation requires assumptions, it is at least mathematically plausible that the social visits could account for the higher infection rates.

Chinese New Year Social Visits Partially Mediate Rice–Wheat Differences. Next, we tested whether regional differences in social visits for Chinese New Year could statistically mediate the relationship between rice and COVID-19 cases. To test this, we ran mediation models using the Mediation package in the program R with bootstrapped confidence intervals based on 500 simulations. We tested mediation with a variable representing the interaction between social visits and travel from Wuhan.[2] This interaction represents the idea that social visits were riskier in places with lots of travel from Wuhan. In contrast, social visits were less risky in places with less travel from Wuhan.

Figure 9 reports the results. The combination of social visits and travel from Wuhan strongly predicted prefectures' COVID-19 cases during Chinese New Year ($B = 0.005$, $p < .001$, $r = .90$), and it significantly mediated the relationship between rice and COVID-19 cases ($B = 0.07$, 95% CI = [.03, 0.14], $p < .001$). The results are consistent with a causal story, although a mediation analysis cannot singlehandedly prove causality.

To be fair, there were probably cases already spreading outside of Wuhan by the time of Chinese New Year. However, the interaction does not assume that there were zero cases outside of Wuhan. Instead, the interaction merely represents the idea that travel from Wuhan was *more* risky than travel from other places. However, to be thorough, we also tested the mediation without the interaction, and the mediation remained significant (Supplemental Figure S1).

Discussion

This study found evidence that COVID-19 spread more during Chinese New Year in regions with a legacy of rice farming. The fact that the center of the outbreak was on China's rice–wheat border allowed for a unique opportunity to test how the virus spread both in rice and wheat areas. On average, rice–farming prefectures suffered three times more COVID-19 cases per capita than wheat-farming prefectures.

Our explanation is that historical rice farming shaped an interdependent culture, with tight social norms and low relational mobility (Talhelm & English, 2020; Talhelm et al., 2014). The social norms and low mobility mattered during Chinese New Year, when social visits are the norm, and when the virus was just starting to spread widely around the country. Data showed that rice–wheat differences in social visits for Chinese New Year mediated the effect of rice on COVID-19 cases.

The idea that this effect was specific to the social obligations of Chinese New Year fits with the finding that rice areas of China suffered *fewer* COVID-19 cases afterwards. Rice areas suffered fewer COVID-19 cases *after* Chinese New Year 2020 and even during Chinese New Year 2021 and 2022, when anti-COVID norms had strengthened. This fits with the finding that rice-farming countries around the world had fewer cases and deaths (Talhelm et al., 2022). Therefore, rice cultures tended to be better at preventing COVID-19, but their strong social ties backfired in the context of the Chinese New Year holiday.

An Exception to Interdependent Cultures' Strength in Controlling COVID

These findings sketch out a boundary condition—an exception—to the outperformance of interdependent cultures documented in previous studies. Previous studies have documented fewer COVID-19 cases and deaths in interdependent cultures than in individualistic countries, even controlling for economic development, urbanization, population age, and other possible confounds (Canatay et al., 2021; Kumar, 2021). Interdependent cultures tend to have tight social norms and low relational mobility, which are both linked to fewer COVID-19 cases and deaths (Gelfand et al., 2021; Salvador et al., 2020).

However, researchers in Japan have argued that there are other aspects of tight, interdependent cultures that could make it harder to contain COVID-19 (Kito & Maeda, 2021). Kito and Maeda (2021) argued that tight social ties motivated people in Japan to avoid testing to avoid the social stigma of testing positive. The stronger social stigma also could have motivated people in interdependent cultures to hide their positive test results and ignore calls from contract tracers. Even if interdependence results in fewer COVID-19 cases overall, it is worth investigating whether interdependence also encourages some counter-productive responses like hiding positive tests.

Subsistence Style and Ecological Theories of Culture

These findings contribute to theory in several ways. For one, the data here reinforce the idea that Han China is not just a single culture (Talhelm et al., 2014). Instead, there are meaningful cultural differences within China. China provides a useful opportunity for researchers to test for cultural differences while holding national variables constant, such as national health care systems, laws, and enforcement. These findings also highlight the cultural diversity within nations, making a small contribution to reducing the reliance on Western samples in social psychology (Rad et al., 2018).

The findings here suggest that it is important to test cultural differences over time, rather than assuming that cultural differences are the same across time. For example, COVID-19 spread faster in cultures with more mobile relationships (Salvador et al., 2020). However, data tracking mobility over time found that relationally mobile cultures actually cut their mobility *more* over time as outbreaks worsened (Freeman & Schug, 2021). Cultures are not static. Cultures differ not just in their long-term characteristics but also in how they respond over time.

The findings here contribute to subsistence theories of cultural differences (Ang & Fredriksson, 2017; Fincher et al., 2008). Subsistence theories argue that how societies made a living shaped their cultures (an overview of ecological theories of culture: Talhelm & Oishi, 2019). Looking at long-run historical factors helps the field move beyond documenting cultural differences and onto tracing an ultimate cause (ecology) to a distal cause (historical rice farming) to a proximal mechanism (social norms). Even though rice farming is rooted in thousands of years in the past, it can leave an enduring effect on cultures, even shaping reactions to a disease that was unknown before 2019 (Nisbett & Cohen, 2018; Talhelm et al., 2014).

Limitations

This study has several limitations worth noting. One limitation is that the data on social visits for Chinese New Year were for 2010, not from the year of the pandemic. The Chinese New Year cell phone travel data from 2019 and 2020 suggest that rice–wheat differences in holiday practices persisted through 2020. However, we do not have direct evidence for social visits in 2020. It may be difficult to get people to report social visits for 2020 because reporting visits might carry stigma.

Similarly, we do not have direct data on people's perceptions of the obligation to make social visits for Chinese New Year. The data showing more social visits in rice areas are evidence of a descriptive norm. An earlier study found evidence that people in rice areas perceive tighter social norms in general than people in wheat areas (Talhelm & English, 2020). However, we do not have data on perceptions of this social visiting norm in particular.

Another limitation is that we rely on publicly available COVID-19 test data. Some people have expressed skepticism of China's COVID-19 data ("Covid-19 Deaths in Wuhan Seem Far Higher Than the Official Count," 2021). However, an independent estimate of COVID-19 underreporting around the world through 2021 from the Institute for Health Metrics and Evaluation found China had among the world's lowest underreporting. In addition, China issued national guidelines for diagnosing COVID-19 on January 22, 2020, before any of our comparisons. This suggests that diagnosis across China had a common standard. However, we cannot completely rule out underreporting.

Constraints on Generalizability

It is also important to consider constraints on how generalizable these findings are. We explicitly theorize that the worse outcomes in rice areas were limited to the early days of the pandemic for a few reasons. First, cutting social ties may have been particularly difficult in the beginning of the pandemic, before people widely agreed that COVID-19 was a serious threat. Over time, societies had time to build widespread agreement that COVID-19 was a threat. Once societies agreed on the threat, then even low-mobility cultures could loosen the social obligations of Chinese New Year.

Second, we do not know whether this risk of interdependent ties will replicate in other cultures. Interdependent cultures tend to have tight social norms and low relational mobility (Gelfand et al., 2011; Talhelm et al., 2022, p. 10), but there are exceptions. Latin America sticks out for its combination of interdependence and high relational mobility (Krys et al., 2021; Thomson et al., 2018).

The social obligation to visit family and friends during important holidays might require the *combination* of tight norms and low relational mobility. These two go together in China's rice-farming areas but in not all interdependent cultures. It would be worth testing whether social ties in more interdependent Latin American communities in the U.S. or Middle Eastern immigrant communities in the European Union might have caused localized outbreaks during important holidays.

Implications for Public Health

The data here suggest an exception to the general finding that interdependent cultures were more successful at containing COVID-19. The social demands of Chinese New Year created more public health risk for people in areas of China with a stronger tradition of visiting family and friends for Chinese New Year. These results document one way in which cultural practices affect public health. Public health messaging and strategies might work better if they recognize the social demands of different cultures, even within the same nation.

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Supplemental Material

Supplemental material is available online with this article.

Notes

1. For example, this site lists cases for Beijing: http://wjw.beijing.gov.cn/wjwh/ztzl/xxgzbd/.
2. We calculated this by multiplying the Chinese New Year social visit variable by the measure of travel from Wuhan.

References

Ang, J. B., & Fredriksson, P. G. (2017). Wheat and family ties. *European Economic Review*, *100*, 236–256.

Canatay, A., Emegwa, T. J., & Hossein Talukder, M. F. (2021). Critical country-level determinants of death rate during Covid-19 pandemic. *International Journal of Disaster Risk Reduction*, *64*, 102507.

Covid-19 deaths in Wuhan seem far higher than the official count. (2021, May 30). *The Economist*. https://www.economist.com/graphic-detail/2021/05/30/covid-19-deaths-in-wuhan-seem-far-higher-than-the-official-count

Curran, P. J., West, S. G., & Finch, J. F. (1996). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological Methods*, *1*(1), 16–29.

de Guzman, C. (2023, January 20). Lunar new year: 5 Things to know about the holiday. *Time*. https://time.com/6248736/lunar-new-year-celebrations/

Dong, X., Talhelm, T., & Ren, X. (2018). Teens in rice county are more interdependent and think more holistically than nearby wheat county. *Social Psychological and Personality Science*, *10*(7), 966–976.

English, A. S., Talhelm, T., Tong, R., Li, X., & Su, Y. (2022). Historical rice farming explains faster mask use during early days of China's COVID-19 outbreak. *Current Research in Ecological and Social Psychology*, *3*, 100034.

Fang, H., Wang, L., & Yang, Y. (2020). Human mobility restrictions and the spread of the novel coronavirus (2019-nCov) in China. *Journal of Public Economics*, *191*, 104272.

Fei, X. (1945). *Earthbound China: A study of rural economy in Yunnan*. University of Chicago Press.

Fincher, C. L., Thornhill, R., Murray, D. R., & Schaller, M. (2008). Pathogen prevalence predicts human cross-cultural variability in individualism/collectivism. *Proceedings Biological Sciences*, *275*, 1279–1285.

Freeman, J. D., & Schug, J. (2021). Freedom to stay-at-home? Countries higher in relational mobility showed decreased geographic mobility at the onset of the COVID-19 pandemic. *Frontiers in Psychology*, *12*, Article 648042.

Gelfand, M. J., Jackson, J. C., Pan, X., Nau, D., Pieper, D., Denison, E., Dagher, M., Van Lange, P., Chiu, C.-Y., & Wang, M. (2021). The relationship between cultural tightness-looseness and COVID-19 cases and deaths: A global analysis. *The Lancet Planetary Health*, *5*(3), e135–e144.

Gelfand, M. J., Raver, J. L., Nishii, L., Leslie, L. M., Lun, J., Lim, B. C., Duan, L., Almaliach, A., Ang, S., Arnadottir, J., Aycan, Z., Boehnke, K., Boski, P., Cabecinhas, R., Chan, D., Chhokar, J., D'Amato, A., Ferrer, M., Fischlmayr, I. C., . . . Yamaguchi, S. (2011). Differences between tight and loose cultures: A 33-nation study. *Science*, *332*(6033), 1100–1104. https://doi.org/10.1126/science.1197754

Gong, W., Zhu, M., Gürel, B., & Xie, T. (2021). The lineage theory of the regional variation of individualism/collectivism in China. *Frontiers in Psychology*, *11*, Article 596762.

Grossmann, I., & Varnum, M. E. W. (2015). Social structure, infectious diseases, disasters, secularism, and cultural change in America. *Psychological Science*, *26*, 311–324.

Kito, M., & Maeda, Y. (2021). The effect of relational mobility on the early and late stages of the COVID-19 outbreak: Discussion from the socioecological perspective. *Shinrigaku Kenkyu*, *92*(5), 473–481.

Krys, K., Vignoles, V. L., De Alameida, I., & Uchida, Y. (2021). Outside the 'cultural binary': Understanding why Latin American collectivist societies foster independent selves. *Perspectives on Psychological Science*, *17*(4), 1166–1187.

Kumar, R. (2021). Impact of societal culture on Covid-19 morbidity and mortality across countries. *Journal of Cross-cultural Psychology*, *52*(7), 643–662.

Lauer, S. A., Grantz, K. H., Bi, Q., Jones, F. K., Zheng, Q., Meredith, H. R., Azman, A. S., Reich, N. G., & Lessler, J. (2020). The incubation period of Coronavirus Disease 2019 (COVID-19) from publicly reported confirmed cases: Estimation and application. *Annals of Internal Medicine*, *172*(9), 577–582.

Lauerman, J. (2020, February 28). Coronavirus spread in China mostly among families, WHO says. *Bloomberg*. https://www.bloomberg.com/news/articles/2020-02-28/coronavirus-spread-in-china-mostly-among-families-report-says

Lu, J. G., Jin, P., & English, A. S. (2021). Collectivism predicts mask use during COVID-19. *Proceedings of the National Academy of Sciences*, *118*(23), Article e2021793118.

Nisbett, R. E., & Cohen, D. (2018). *Culture of honor: The psychology of violence in the South*. Routledge.

Noblit, G. (2022). *The origin and evolution of Chinese lineages*. Harvard University.

Rad, M. S., Martingano, A. J., & Ginges, J. (2018). Toward a psychology of Homo sapiens: Making psychological science more representative of the human population. *Proceedings of the National Academy of Sciences*, *115*(45), 11401–11405.

Salvador, C. E., Berg, M. K., Yu, Q., San Martin, A., & Kitayama, S. (2020). Relational mobility predicts faster spread of COVID-19: A 39-country study. *Psychological Science*, *31*(10), 1236–1244.

Schug, J., Yuki, M., & Maddux, W. (2010). Relational mobility explains between- and within-culture differences in self-disclosure to close friends. *Psychological Science*, *21*(10), 1471–1478.

Talhelm, T., & English, A. S. (2020). Historically rice-farming societies have tighter social norms in China and worldwide. *Proceedings of the National Academy of Sciences*, *117*(33), 19816–19824.

Talhelm, T., Lee, C.-S., English, A. S., & Shuang, W. (2022). How rice fights pandemics: Nature-crop-human interactions shaped COVID-19 outcomes. *Personality and Social Psychology Bulletin*.

Talhelm, T., & Oishi, S. (2018). How rice farming shaped culture in Southern China. In A. K. Uskul & S Oishi. (Eds.), *Socioeconomic environment and human psychology* (pp. 53–76). Oxford University Press.

Talhelm, T., & Oishi, S. (2019). Culture and ecology. In D. Cohen & S Kitayama. (Eds.), *Handbook of cultural psychology* (pp. 119–143). Guilford Press.

Talhelm, T., Zhang, X., & Oishi, S. (2018). Moving chairs in Starbucks: Observational studies find rice-wheat cultural differences in daily life in China. *Science Advances*, *4*, Article eaa8469.

Talhelm, T., Zhang, X., Oishi, S., Shimin, C., Duan, D., Lan, X., & Kitayama, S. (2014). Large-scale psychological differences within China explained by rice versus wheat agriculture. *Science*, *344*, 603–608.

Thomson, R., Yuki, M., Talhelm, T., Schug, J., Kito, M., Ayanian, A. H., Becker, J. C., Becker, M., Chiu, C., Choi, H.-S., Ferreira, C. M., Fülöp, M., Gul, P., Houghton-Illera, A. M., Joasoo, M., Jong, J., Kavanagh, C. M., Khutkyy, D., Manzi, C., . . .Visserman, M. L. (2018). Relational mobility predicts social behaviors in 39 countries and is tied to historical farming and threat. *Proceedings of the National Academy of Sciences*, *115*(29), 7521–7526.