Culture and Contagion: Individualism and Compliance with COVID-19 Policy*

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Abstract

Places where geographic mobility declined more rapidly have seen fewer cases of COVID-19. Despite this fact, there is significant variation in people's compliance with the lockdown measures introduced by governments in order to curb the spread of the virus. In this paper, we show that much of this variation can be explained by different cultural traits. Specifically, we advance the hypothesis that individualism, which rewards deviant behaviour, makes government intervention harder, whereas collectivism, which emphasises the wellbeing of the group, makes collective action easier. We find support for these ideas across countries, within the United States, as well as across cities in China. Our findings show that people were less abiding by the lockdown rules in places with greater prevalence of individualistic cultural traits. We conclude that cultural factors play a critical role in successful policy implementation.

Keywords: COVID-19, Individualism, Social distancing, Culture, Public Policy, Compliance

JEL classification: H11; H12; I18; Z1

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1 Introduction

Populations around the world vary significantly in their psychological traits (Henrich et al., 2001; Nisbett, 2004; Nisbett et al., 2001). For example, people from Western Europe and their cultural descendants in North America stand out as being more individualistic, less conformist and obedient, while exhibiting a higher degree of in-group loyalty and nepotism (Bond and Smith, 1996; Gächter and Schulz, 2016; Henrich et al., 2001; Herrmann et al., 2008; Schulz et al., 2019; Talhelm et al., 2014). Among the many dimensions of cultural variation, cross-cultural psychologists see the individualism-collectivism distinction as the main divider (Heine, 2010). An important source of this variation relates to societies historical exposure to disease-causing pathogens.[1] Indeed, geographies with greater pathogen prevalence have developed cultural norms that serve as buffers against pathogen transmission (Gangestad and Buss, 1993; Quinlan, 2007; Schaller and Murray, 2008), making them more collectivist, since deviance from those norms poses a contagion risk to the community (Fincher et al., 2008). Conformity, in contrast, reduces the risk of spreading the disease.[2]

Countries around the world have fared very differently during the COVID-19 pandemic. For example, places where geographic mobility declined more rapidly have seen fewer cases (Glaeser et al., 2020). Yet despite this, there is wide cross-country heterogeneity in people's compliance with the lockdown measures introduced by their governments. For instance, at the peak of the first wave of the pandemic in April 2020, when most national governments imposed strict stay-at-home requirements, time spent at home increased by forty percent in some countries, but just by around ten percent in others.[3]

Against this background, we examine the role of cross-cultural differences in explaining this variation. Our hypothesis goes as follows. Collectivism, which encourages conformity and sanctions deviant behaviour, makes collective action easier since individuals emphasize the wellbeing of the group to a greater degree. Individualism, on the other hand, which emphasises

[1] To be sure, the literature has emphasized other sources of variation in individualistic cultural traits. For instance, Schulz et al. (2019) shows that the dissolution of kinship structures following the family policies of the Latin Church (e.g. bans on cousin marriage), fostered individualism. In addition, Talhelm et al. (2014) documents how the prevalence of rice and wheat farming has shaped the geography of individualistic psychology. See also Henrich (2020) for an overview of the literature.

[2] One example is cultural norms pertaining to food preparation (Sherman and Billing, 1999)

[3] This is shown in Figure B1 of the online appendix.

personal freedom and achievement, provides greater incentives for standing out as it rewards deviance (Gorodnichenko and Roland, 2011a, 2020). This makes collective action harder, such as coordinating a coherent response to a pandemic. Indeed, studies show that people are much less supportive of government interventions in more individualistic societies (Pitlik and Rode, 2016).

Consistent with our hypothesis, our findings show that places with a greater prevalence of individualistic cultural traits saw less compliance with the stay-at-home requirements introduced by their governments. Our results are robust across a host of specifications across countries, but also when exploiting within-country variation in culture, policy and mobility in the two largest economies: the United States and China.[4] Crucially, our analysis based on peoples self-reported ancestry in the United States allows us to exclude the impact of all factors except those operating through some form of intergenerational transmission. Consistent with our cross-country results, we find that the historic prevalence of individualistic cultural traits predicts lower levels of compliance with the lockdown measures taken across US counties today. Finally, because a society's cultural traits could be influenced by sociopolitical and geopolitical factors, we further explore the relationship between culture and mobility in China. Despite China's unique economic and political model, we find that our proxy for collectivism predicts more compliance with stay-at-home requirements across Chinese cities, reinforcing the external validity of our findings.

Our paper adds to a growing literature on compliance with public health policy during the COVID-19 pandemic. For example, Wright et al. (2020) argue that economic factors have played an important role in shaping peoples compliance with the lockdown measures introduced across the United States, showing that people in low-income areas were less abiding by those measures relative to their counterparts in high-income cities. Meanwhile, other papers have gone beyond economic factors and examined the role of culture and values in peoples compliance with COVID-19-related public health recommendations. In particular, Bazzi et al. (2020) argue that a higher incidence of individualistic cultural traits undermines collective action and hampered the response to the COVID-19 pandemic. However, their analysis is con-

[4]The United States and China are the largest economies in the world in terms of Gross Domestic Product (GDP). They also account for over 20 percent of the worlds population.

fined to the United States, which Hofstede (2001) shows is the most individualistic country in the world, making it a potential outlier. Finally, Bargain and Aminjonov (2020) provide evidence that within Europe, people complied more with mobility restrictions in regions characterised by higher trust, while Barrios et al. (2020) focus on the role of civic capital in determining compliance with COVID-19 policy. In Frey et al. (2020), we show that trust and civic capital are both closely linked to the prevalence of democratic institutions.[5] In this paper, in contrast, we document that collectivism, which is prevalent in autocratic countries like China, but also in democratic countries like Taiwan and South Korea, has a strong independent relationship with people's compliance with COVID-19 policy.

The remainder of this paper is structured as follows. Section 2 discusses our data and provides some descriptive statistics. Section 3 discusses our empirical methodology and presents the key findings from our country-level analysis. Section 4 zooms in on the United States, exploring how individualism shaped compliance with Covid-19 policy across counties. Section 5 turns to China, examining the link between policy compliance and cultural tightness. Finally, in section 6, we provide some conclusions.

2 Data and Descriptive Statistics

For our country-level analysis, we use data on lockdown orders matched with daily data on geographic mobility across 111 countries, between February 15, 2020 and June 15, 2020.[6] Our dependent variables are taken from Google's Mobility Reports and captures daily changes in both time spent at home and patterns of geographic mobility, compared to the median value for the corresponding day of the week during the period between the 3rd of January and the 6th of February 2020. Our baseline policy variable—taken from the Oxford COVID-19 Government Response Tracker (OxCGRT)—is a dummy taking the value 1 if a government imposes a stay-at-home order by law (Hale et al., 2020).[7] To capture differences in cultural traits across coun-

[5] We note that trust and individualism are related. For example, studies show that individualistic cultures are more trusting towards strangers, whereas trust in collectivistic societies is more confined to the in-group (see Henrich, 2020, for an overview).

[6] We use all available data on mobility and policy up until this point in time.

[7] Our results remain similar if we only consider stay-at-home requirements mandated by law or consider official recommendations separately. Tables are available upon request.

tries, we employ the widely used individualism-collectivism measure from Hofstede (2001). The individualism measure captures the extent to which people in a society believe that individuals are responsible for taking care of themselves as opposed to being loyal to a cohesive group. Countries ranking higher on the individualism scale value personal freedom, whereas people in lower-ranked countries value conformity. The measure is based on a broad array of survey questions and has been validated in numerous studies (Gorodnichenko and Roland, 2011b).[8]

To shed some light on the relationship between individualism and compliance with COVID-19 policy, we calculate cross-country changes in time spent at home as well as in patterns of geographic mobility, before and after the implementation of any stay-at-home measures. Then, we estimate the differential changes in these variables in individualistic societies relative to others. Consistent with our hypothesis, we find people's compliance with the stay-at-home requirements introduced by their governments to be lower in countries with individualistic cultural traits. In Figure B2 of the online appendix, we show that our estimated elasticities of time spent at home and the individualism-collectivism measure from Hofstede (2001) are negatively correlated (Panel A). Conversely, we note that our mobility elasticities are positively correlated with the prevalence of individualism (Panel B). While these relationships are by no means conclusive, they provide suggestive evidence that individualistic societies are less likely to abide by the lockdown rules. In Section 3, we further probe this relationship.

We next zoom in on the United States. For this part of our analysis, we exploit differences in past patterns of immigration to construct measures of individualism for 722 commuting zones across the mainland of the United States (see 4.1). Using micro-level Census data on self-reported ancestry, we are able to characterise the cultural origins of US communities. Matched with county-level data from Google's Mobility Reports and newly collected data on stay-at-home requirements across US states, we follow a large literature on cultural evolution (Heine, 2007; Henrich, 2017; Henrich et al., 2001; Schulz et al., 2019) in documenting a remarkable persistence in cultural traits across generations. Specifically, for each commuting zone, we calculate the composition of the population in terms of ancestry.[9] Based on a commuting zone's

[8] A detailed description of the variables and data sources can be found in the online data appendix A.

[9] We also experiment with a measure of individualism based on people's country of origin (birthplace), which

population composition, we obtain an estimate of the incidence of individualism by aggregating Hofstede's measure from the ancestors' country of origin.[10] Figure 1 shows a high degree of heterogeneity in the incidence of individualism across US counties (see 4.1 for details on the construction of the Figure). In our analysis, we exploit this variation as well as the fact that different states imposed stay-at-home measures at different times. In Figure B3 of the online appendix, we document a strong negative relationship between the stay-at-home elasticity to the lockdown measures taken and the prevalence of individualism across US commuting zones (Panel A). As expected, we also find a negative correlation between the elasticity of mobility and the prevalence of individualistic cultural traits (Panel B), which we investigate further in section 4.[11]

It must be noted, however, that China is not included in Google's Mobility Reports, and thus excluded from the analysis above. To assess whether our findings are also applicable to the Chinese context, we use data on daily mobility provided by Baidu (see A.1).[12] In addition, because lockdown measures across Chinese cities are missing in the OxCGRT database, we create a novel dataset on local lockdown orders across China, as outlined in the appendix. Moreover, since Hofstede's measure of individualism is unavailable for China, we use cultural tightness from Gelfand et al. (2011) as an inverse proxy of individualism (i.e., collectivism).[13] Cultural tightness is defined as "the degree to which a society is characterised by rules and norms and the extent to which people are punished or sanctioned when they deviate from these rules and norms" (Chua et al., 2019). Despite being conceptually different from collectivism, we find that across the countries for which data are available, the tightness measure is negatively correlated to Hofstede's individualism measure.[14] Figure B4 of the online appendix shows that mobility was more elastic to lockdown measures at the local level in culturally tight Chinese provinces, as our hypothesis predicts.[15]

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delivers similar results.

[10]See also Berger and Engzell (2019).

[11]The results from the county/commuting zone-level analysis are averaged at the state-level for visualisation.

[12]Given these data limitations, China is not included in Figure B2.

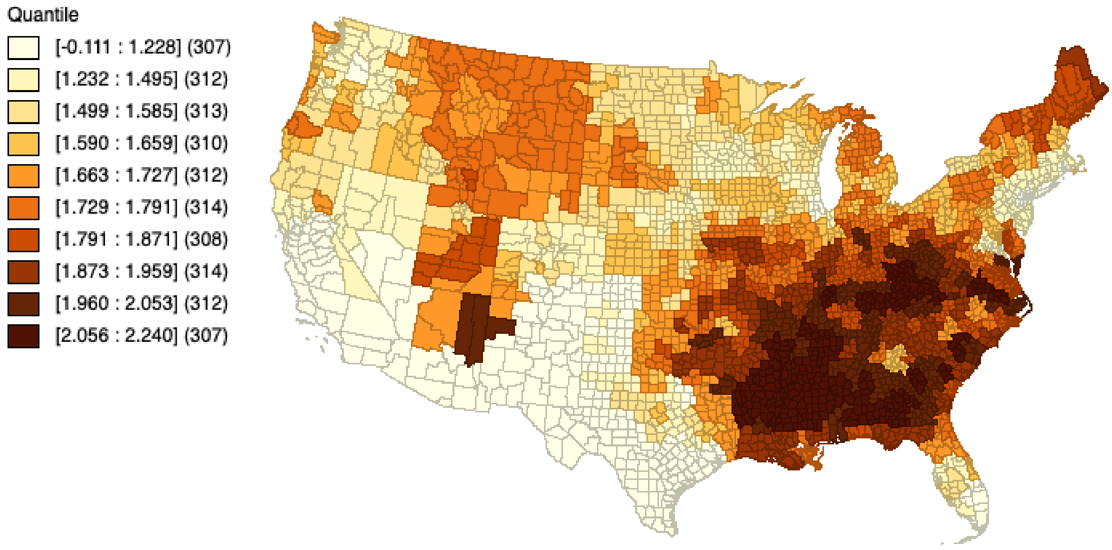
[13]Scholars have documented significant cross-country variation in cultural tightness (Gelfand et al., 2011), as well as within country variation in China (Chua et al., 2019). A link between cultural tightness and COVID-19 cases in the United States has also been established (Van Bavel et al., 2020).

[14]In our data, the correlation between the two variables is approximately equal to -0.4.

[15]For China, mobility data vary at the city-level, while data on tightness vary at the province level. In Figure B4, city-level elasticities are averaged at the province-level to improve the readability of the figure.

In other words, the descriptive evidence provided so far is consistent with our hypothesis that differences in cultural traits across and within countries help explain the heterogeneity in compliance with the lockdown measures introduced by national and local governments around the world. We next turn to exploring the robustness of the above described results in greater detail.

Figure 1: Prevalence of individualistic cultural traits across US counties.



This figure shows how each county is positioned in the total distribution of the individualism measure (which varies at the commuting zone-level). Darker shades correspond to a higher incidence of individualistic cultural traits (see 4.1 for details on the construction of the figure). Sources: authors' own calculations based on Hofstede (2001); IPUMS USA; David Dorn's data page: https://www.ddorn.net/data.htm.

3 Individualism and Policy Compliance: A Country-level Analysis

To formally study the relationship between the mobility restrictions introduced by governments around the world and changes in actual mobility, we estimate OLS regressions at different levels of aggregation. We first turn to our cross-country analysis to assess whether our hypothesis broadly holds. To mitigate concerns about these estimates being driven by other country-specific factors, we next move on to studying within-country variation in culture, policy and mobility in the United States and China. By zooming in on these particular countries, we are able to explore whether our hypothesis are relevant across very different political systems, which might reward different types of behaviour. For example, the US Constitution, which emphasises individual freedom and liberty, would make a Chinese-style lockdown—involving involuntary isolation at quarantine centres—impossible.

3.1 Empirical Strategy

In this part of our analysis, we exploit the variation in policy and mobility across countries and over time. Our regressions are based on the following specification:

$$M_{c,t,m} = \beta_0 + \beta_1 \Phi_{c,t-1} + \beta_2 \Big[\Phi_{c,t-1} \times X_c\Big] + \beta_3 \Theta_{c,t} + u_{c,m} + u_t + \varepsilon_{c,t,m} \qquad (1)$$

where, $M_{c,t,m}$ is our mobility index in country c, at date t, in mobility category m. The variable $\Phi_{c,t-1}$ is our policy index, which is lagged by one day in order to ensure that changes in policy are known to the population.[16] In addition, as discussed in appendix A.1, we take advantage of the fact that Google provides mobility indexes for a host of categories:

$$m = \{\text{workplace, grocery, transit, retail and entertainment, residential, park}\}$$

For example, one concern is that mobility in parks could be systematically higher in coun-

[16]Results are very similar if we impose a lag of three days, or use the contemporaneous value of the index.

tries with a larger number of parks, or a temperate climate. Thus, in equation (1) we include country-mobility category fixed effects, $u_{c,m}$, which allows us to purge our estimates from constant unobserved characteristics of each particular mobility category in a given country. Country fixed effects also allows us to exclude any bias arising from country-specific characteristics, including differences in the coverage and quality of the mobility data.

In equation (1), the coefficient of interest is β_2, which measures the differential impact of lockdown measures for countries characterised by different levels of individualism. We measure individualism based on either Hofstede' scale or a measure of obedience, which should be highly correlated to collectivism, as it similarly encourages tradition and conformity.[17] To ease interpretation, we normalise the two variables to have zero mean and unitary standard deviation.

Our specifications include the interaction between policy stringency (X_c) and i) the logarithm of real GDP per capita; ii) the number of cellphone subscriptions in the population; iii) a measure of the strength of democratic institutions; iv) a dummy for whether a country had experience in dealing with previous epidemics; and v) the log-number of daily confirmed cases. Such controls further mitigate concerns that systematic differences in economic development and institutions (Wright et al., 2020), as well as differential trajectories of the spread of the virus between individualistic and collectivistic countries, are driving our results.[18] Finally, to account for the potential impact of complementary policies, we include measures of testing intensity and the extent of contact tracing in the vector $\Theta_{c,t}$.[19]

[17] Our measure of obedience is based on data from the World Value Survey. See the online appendix and Frey et al. (2020) for details.

[18] Including confirmed cases helps mitigating the concern that differences in policy compliance might be driven by network structure (some societies being more interconnected than others), which in turn might shape the spread of the virus.

[19] To construct Figure B2, we estimate country-specific mobility elasticities to changes in policy using the following linear model:

$$M_{c,t,m} = \delta_0 + \delta_1 \Phi_{c,t-1} + \sum_{k=1}^{C} \delta_{2k} \left[\Phi_{c,t-1} \times u_k \right]$$
$$+ u_{c,m} + u_t + \varepsilon_{c,t,m}$$

where, C is the total number of countries and $u_k = 1$ when $k = c$. The elasticity of mobility to changes in policy stringency for country c' is given by:

$$\frac{dM_{c',t,m}}{d\Phi_{c',t}} = \delta_1 + \delta_{2c'} u_{c'}$$

3.2 Country-level Results

Before turning to our OLS results based on equation (1), we study whether the probability of implementing lockdown measures depend on cultural traits. To do so, we regress a dummy equal to 1 if stay-at-home requirements are imposed, on the log of confirmed COVID-19 cases and its interaction with our individualism or obedience measures. We use a probit model in which we control for country and date fixed effects, and we cluster errors at the country-level. The results are shown in Table B1 of the online appendix. As expected, the probability of implementing lockdowns depends on the number of infections in each country. However, we do not find evidence that governments in countries with strong individualistic cultural traits are less likely to lock down (columns 1-2). We also examine whether countries with high obedience scores are more likely to implement stay-at-home requirements (columns 3-4). Again, we find no evidence in support of this hypothesis.

Table 1 presents the results from estimating equation (1) on the time spent in residential places. On average, stay-at-home measures increased the time spent at home by roughly 7.5 percent over the sample (column 1). We note that the increase in time spent at home due to restrictions on movement was muted in countries with stronger individualistic cultural traits, where it was approximately thirty percent lower (column 2). Concerns over omitted variables that might be correlated with cultural traits and mobility are alleviated by the fact that our results are robust to controlling for different levels of economic development, institutional differences, experience with past epidemics, and the number of confirmed COVID-19 cases (column 3). Regardless of the specification, the coefficients of interest are statistically significant.

Table B2 of the online appendix presents the results from regressing mobility indexes, capturing the frequency of visits to a given place, on stay-at-home requirements. On average, stay-at-home measures reduced mobility by roughly 17 percent over the sample period (column 1). We note that the reduction in mobility was relatively muted in countries with stronger individualistic cultural traits, where declines in mobility were approximately twenty-five percent lower (column 2). Adding a full set of controls leaves our results substantially unchanged

A similar strategy is used to compute the state-level elasticities of Figure B3 and the province-level elasticities of Figure B4.

(column 3).

That said, the average effects reported in columns 1-3 hide a great deal of heterogeneity, not least since people move around for different reasons. To capture this, we break down mobility into essential (e.g. grocery shopping) and non-essential travel (e.g. walking in parks), based on the categories provided in the Google Mobility Reports (see A.1). Unsurprisingly, the results of columns 4-9 of Table B2 suggest that restrictions reduced mobility less for essential than for non-essential travel. In other words, cross-cultural differences in mobility are not primarily driven by people in individualistic countries fulfilling more basic needs, but their greater willingness to deviate from stay-at-home measures for non-essential purposes.

We also perform a battery of robustness checks. First, we replace the individualism measure from Hofstede with our obedience variable (see Table B4). Consistent with our hypothesis, lockdown measures increased the time spent at home more in countries at one standard deviation above the average obedience score (column 1). The coefficient of the interaction terms is again statistically significant across all specifications. Columns 2-4 in Table B4 also show that the elasticity of mobility to stay-at-home requirements is lower for essential than for non-essential travel. We note that the reduction in mobility is even larger in countries with higher levels of self-reported obedience.

Second, instead of coding the policy indicator as a dummy equal to 1 if a government requires people to stay at home, we use the original value of the index from OxCGRT.[20] The results are very similar, suggesting that our parsimonious policy indicator, which is easier to interpret than a category variable, appears to capture all the relevant information. As a final robustness check, we also use a broader policy stringency index. This index, which is also taken from the OxCGRT data, is an average of eight sub-indicators. Besides stay-at-home requirements, which we have focused on, it also includes school, workplace and public transport closures, as well as bans on public events and size restrictions on gatherings (see Hale et al. (2020) for further details). Again, we obtain similar results, implying a high correlation among the sub-indicators.[21]

[20]Specifically, the original indicator is equal to zero if no measure is implemented; 1 if the government recommends not leaving the home; 2 if it requires not leaving home for non-essential trips; 3 if it requires not leaving home with minor exceptions.

[21]The tables are available upon request.

Table 1: Individualism and compliance across countries.

	(1) Residential	(2) Residential	(3) Residential
Stay at home index	7.590***	7.125***	2.648
	(0.775)	(0.910)	(3.683)
Stay at home index × individualism		-1.824***	-2.115*
		(0.630)	(1.111)
Observations	15,274	10,882	9,127
R-squared	0.791	0.804	0.799
Country-mobility category FE	yes	yes	yes
Date FE	yes	yes	yes
Policy x controls	no	no	yes

This table presents OLS estimates from regressing time spent at home at the country-level on (the one day-lag of) a dummy taking value 1 if on a given day the government imposed restrictions to stay at home. Column 3 includes interactions between the dummy and: i) the logarithm of real GDP per capita; ii) the number of cellphone subscriptions in the total population; iii) a measure of democracy from the Polity Project, iv) a dummy for experience with previous epidemics, and; v) the log-number of confirmed COVID-19 cases. Errors are clustered at the country-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

3.3 Pre-trends

To check for pre-trends, Figure B7 of the online appendix presents the results of an event study regression. We find no evidence of significant differences in mobility before the announcement of the lockdown measures. At the time of implementation, however, the increase in time spent at home was significantly lower in individualistic countries relative to others, consistent with the regression results in Table 1.

Figure B7, shows that mobility in individualistic countries starts diverging from the others a few days before official implementation. The underlying reason is that in most countries, authorities recommended staying at home several days in advance of any mobility restrictions being put into place. Data provided by Cheng et al. (2020) allows us to measure the number of days between the recommendation and the implementation of the lockdown measures taken. We calculate that the lag between announcement and official implementation of the stay-at-home requirements varies between 1 and 4 days in our sample, which is consistent with the patterns presented in Figure B7.

To make sure that this anticipation effect does not alter our results, in Table B3 we include up to 4 days-lead values of the policy indicator. We note that these results are very similar to our baseline specification. Reassuringly, the presence of rather mild anticipation effects do not seem to substantially bias our baseline regressions.

4 Individualism and Policy Compliance in the United States

To further alleviate the concern that our country-level estimates are driven by country-specific factors, such as institutions, we next exploit within-country variation in culture, policy and mobility across the United States. In the below, we discuss our approach and empirical findings.

4.1 Empirical Strategy

For this part of our analysis, we exploit county-level mobility data as well as regional differences in the demographic composition of the population to construct a measure of individualism for 722 commuting zones (CZs) across the mainland United States. For simplicity, we refer to CZs as "cities", whose boundaries are based on county-level commuting patterns (Tolbert and Sizer, 1996).

Following Berger and Engzell (2019), we rely on public micro data on ancestors' country of origin from the American Community Survey 2014-2018, and map the county-level information to cities using the crosswalk from Autor and Dorn (2013).[22] We then compute the shares of peoples ancestors' country of origin (for which Hofstede's individualism measure is provided) for each city. This allows us to infer the historic exposure of a population to individualistic cultural traits and exclude the impact of all factors except those operating through some form of intergenerational transmission.[23] Formally, the city-specific measure of individualism, Ind_z, is given by:

$$Ind_z = \sum_{j \in z} \sigma_j IND_j$$

where z indexes the city, σ_j is the share of the population with ancestors from country j, and IND_j is the individualism measure of country j.[24] For robustness, we also construct a city-level measure of obedience, Obe_z, following the same approach. Figure B5 of the online appendix provides a glance of the geography of the incidence of obedience in the United States, revealing a wide variation within and across states.

[22]The crosswalk between counties and cities can be found in section E of David Dorn's data page (see https://www.ddorn.net/data.htm).

[23]Our results are robust to using a different approach based on the actual birthplace of individuals in each city.

[24]See Figure 1 for a graphic representation of Ind_z.

Our approach allows us exploit detailed lockdown and re-opening dates at the state-level to study how restrictions on movement impacts mobility across counties *within* states. Thus, in this setting, we are much less concerned about the possibility that economic, institutional or geographical differences might be driving our results. Specifically, our econometric analysis is based on the following specification:

$$M_{y,t,m} = \beta_0 + \beta_1 \Phi_{s,t-1} + \beta_2 \Big[\Phi_{s,t-1} \times X_z\Big] + u_{y,m} + u_t + \varepsilon_{y,t,m} \tag{2}$$

where, $M_{y,t,m}$ is our mobility index in county y (in city z and state s), at date t, and in mobility category m. In equation (2), $\Phi_{s,t-1}$ represents the lockdown dates for each state s. The vector X_z includes Ind_z, and in some specifications, the log of real wage income, to control for the potential systematic correlation between income and cultural traits.[25] The variables u_t and $u_{y,m}$ represent year- and county-mobility category fixed effects, respectively.[26]

4.2 US Regional Results

Table 2 presents our results from estimating equation (2). On average, stay-at-home requirements increased time spent at home by 1.3 percent (column 1). The increase in time spent at home is around seventy percent lower in counties at one standard deviation above the mean individualism score (column 2). However, when we control for wage income in column 3, which is strongly correlated to the incidence of individualism (Gorodnichenko and Roland, 2011a), the interaction coefficient becomes insignificant at conventional levels but remains negative.

Column 4 includes state-date fixed effects, which absorb the potential confounding effect of state-specific unobserved events, such as changes in other types of regulation, the impact of

[25]The variable Ind_z is normalised to have zero mean and unitary standard deviation.

[26] We note that some respondents report the United States as their ancestry. While this is not ideal, since more patriotic Americans might report US ancestry, county-mobility fixed effects absorb local unobserved time-invariant characteristics. This alleviates the concern that people in areas with a stronger sense of patriotism might more likely to falsely report US ancestry, which would bias the calculation of Ind_z. We also note that controlling for the share of US ancestry in each county is not possible, given that such share would be time-invariant and so it would be absorbed by the fixed effect. However, to eliminate any residual concern, we interact the share of US ancestry with the lockdown dates as an additional control. Our baseline results still hold with such a specification. This table is available upon request.

weather conditions, and differences in the spread of COVID-19.[27] Controlling for meteorological events might be important, as the mobility index takes the winter month of January as the reference period. As the weather improves over spring, this could lead to a decrease in time spent at home that is unrelated to mobility restrictions. Similarly, in states with a high incidence of individualistic cultural traits, fewer cases might have induced people to stay home less. Reassuringly, when including state-date fixed effects our results remain intact. Finally, column 5 shows that stay-at-home restrictions increased time spent at home even more in cities with a relatively high incidence of obedience. Thus, alternative measures of individualism (or in this case the inverse of it), point in the same direction: cultural traits are important in explaining why places have fared differentially during the pandemic.[28]

To further assess the robustness of our findings, Table B5 of the online appendix presents the results from estimating equation (2), using mobility changes as the dependent variable, rather than time spent at home. On average, stay-at-home requirements reduced mobility by 3 percent (column 1). Column 2 shows that the reduction was lower in cities with a higher incidence of individualistic cultural traits. We note that this relationship remains statistically significant also when we control for wage income (column 2). We further note that within the US, the reduction in mobility for essential and non-essential travel is roughly the same. However, all interaction coefficients are positive and significant at the 99% level. Finally, when we rely on measures of individualism based on people's country of origin (birthplace), rather then ancestry, this delivers very similar results as shown in Table B6.

5 Cultural Tightness and Policy Compliance in China

In the sections above, we have relied on data from Google's Mobility Reports to calculate changes in time spent at home as well as in patterns of geographic mobility. This dataset, however, does not include China. In the below, we examine whether cultural traits also play an important role in shaping COVID-19 policy compliance in the context of China's unique

[27] As lockdown and re-opening dates are state-specific, we are only able to estimate the interaction terms in this specification.

[28] We note that the coefficients are smaller relative to those of our country-level analysis. This most likely reflects the United States being the most individualist country in the world on Hofstede's scale, meaning that people's compliance with mobility restrictions are generally low in the US.

Table 2: Individualism and compliance across the United States.

	(1) Residential	(2) Residential	(3) Residential	(4) Residential	(5) Residential
Stay at home dates (state-level)	1.295***	1.103***	0.773***		
	(0.199)	(0.208)	(0.181)		
Stay at home dates × individualism		-0.741***	-0.228	-0.746***	
		(0.231)	(0.138)	(0.154)	
Stay at home dates × obedience					0.477**
					(0.227)
Observations	139,009	139,009	139,009	138,847	138,847
R-squared	0.916	0.918	0.922	0.956	0.956
County FE	yes	yes	yes	yes	yes
Date FE	yes	yes	yes	yes	yes
State-date FE	no	no	no	yes	yes
Policy x log wages	no	no	yes	yes	yes

The table presents OLS estimates from regressing time spent at home at the county-level on (the one day-lag of) a dummy taking value 1 if on a given day, the government imposed people to stay at home. Columns 3, 4 and 5 include interactions between the dummy and the logarithm of wage income per capita. Columns 4 and 5 include state-date fixed effects. The individualism measure is obtained by summing up country-level measures weighted by the share of ancestors' country of origin. The obedience measure is derived analogously. Errors are clustered at the state-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

economic and political model. By compiling a novel dataset for China, we are able to further assess the external validity of our findings.

5.1 Empirical Strategy

For our analysis, we exploit policy variation across Chinese cities as well as province-level differences in cultural traits.[29] As we do not have regional data on the incidence of individualism across China, we proxy collectivism with cultural tightness, following Chua et al. (2019). In Figure B6 of the online appendix, we show that tightness and individualism are inversely related (correlation = -0.38) in a cross-section of countries.

Our econometric analysis is based on the following specification:

$$M_{i,t} = \beta_0 + \beta_1 \Phi_{i,t-1} + \beta_2 \Big[\Phi_{i,t-1} \times X_p\Big] + u_i + u_{p,t} + \varepsilon_{i,t} \tag{3}$$

where, $M_{i,t}$ is our mobility index in city i (in province p), at date t. We rely on data provided by Baidu, which unlike the Google Mobility Reports does not have any breakdown by mobility categories (see the online appendix A.1). Thus, we focus on aggregate trends in mobility. Specifically, model (3) exploits variation in measured cultural tightness across

[29]Thus, while we exploit state variation in lockdown dates and city's variation in individualism and mobility in the US analysis, here policy and mobility vary at the city-level and culture at the province-level.

Chinese provinces, which is included in X_p, interacted with the city-level policy, $\Phi_{i,t-1}$. The vector X_p includes the log of city-level GDP per capita in some specifications to control for the potential systematic correlation between income and cultural incidence (Gorodnichenko and Roland, 2011a). We also include province-date fixed effects, $u_{p,t}$, to control for residual factors correlated to mobility and culture that might bias our coefficients, such as differences in the spread of the virus across provinces. Given that there are only 29 provinces, we chose not to cluster errors at the province-level.

5.2 Chinese City-level Results

Table 3 presents the results from estimating model (3) with OLS. We find that stay-at-home requirements reduced mobility much more in cities belonging to culturally tight provinces. Our estimates suggest that stay-at-home restrictions reduced mobility by twenty-five percent on average (column 1), while in provinces characterised by tighter cultural traits, mobility declined by forty percent. Thus, consistent with our hypothesis, mobility fell sixty percent more in tight provinces relative to others. Column 3 shows that our coefficients are unchanged when we control for city-level GDP per capita. The size of the estimated coefficients presented in Table 3 suggest that compliance with mobility restrictions was higher in China overall than in the United States (see Table 2). This speaks to the intuition that Chinese citizens are generally more collectivist than their American counterparts, though it might also partly reflect more severe sanctions being imposed on violations of stay-at-home requirements by the Chinese authorities.

Table 3: Cultural tightness and compliance across China.

	(1) Mobility	(2) Mobility	(3) Mobility
Stay at home dates (city-level)	-24.301***	-24.589***	-23.726***
	(3.323)	(0.897)	(0.443)
Stay at home dates $\times$ cultural tightness		-14.731***	-13.927***
		(1.416)	(0.324)
Observations	38,430	38,430	11,956
R-squared	0.931	0.931	0.961
City FE	yes	yes	yes
Province-date FE	yes	yes	yes
Policy x log GDP	no	no	yes

The table presents OLS estimates from regressing changes in mobility at the city-level on city-specific lockdown dates. The tightness measurefor each province is taken from Chua et al. (2019) (see A.3 for details).

6 Discussion and Implications

Scholars have documented large and consistent deviations from what textbook representations of Homo economics would predict (Camerer and Malmendier, 2007; Fehr and Gächter, 2000; Roth et al., 1991). As observed in Henrich et al. (2001), many people "are willing to reward those who act in a cooperative manner while punishing those who do not even when these actions are costly to the individual." How cooperation is rewarded, however, depends on cultural traits, which vary significantly across countries (Gelfand et al., 2011; Heine, 2010; Henrich et al., 2010; Schulz et al., 2019). These differences have been traced back to numerous historical events including the rise of agriculture (Nisbett et al., 2001; Talhelm et al., 2014), the family policies of the Latin Church (Schulz et al., 2019), and the differential exposure to disease-causing pathogens (Fincher et al., 2008). Whatever the source of cultural variation today, a key message from this research is that culture is highly persistent even at very long horizons, as people socially transmit helpful behaviour-shaping knowledge and information across generations (Boyd and Richerson, 1988; Henrich, 2017).

In this article we have shown how cultural factors have shaped contemporary public policy outcomes, in terms of peoples compliance with the lockdown rules introduced by governments around the world to contain the spread of COVID-19. Taking our findings seriously implies acknowledging the limits policymakers face in altering peoples behaviour when history casts a long shadow. That said, our findings should not be taken to suggest that the policies themselves do not matter. This research has shown that lockdown measures have significantly contributed to reduce mobility and enact social distancing—an essential tool for curbing pandemics (Glaeser et al., 2020). Nonetheless, it is easy to arrive at misleading conclusions about the effectiveness of different policies without accounting for the role of culture. Our study suggest that a realistic understanding of the role of cultural factors is likely to be critical for successful policy implementation.

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Online Appendix (not for publication)

A Data

This section describes the data sources and variables used in our analysis, which are summarised in Table A1.

A.1 Mobility Data

We build a dataset allowing us to trace changes in the movement of people between February 15, 2020 and June 15, 2020. Our main source of mobility data are Google's Community Mobility Reports from which data are collected for 128 countries and US counties. The Mobility Reports provide daily data on Google Maps users who have opted-in to the "location history" in their Google accounts settings. The reports calculate changes in movement compared to a baseline, which is the median value for the corresponding day of the week during the period between the 3rd of January and the 6th of February 2020.[30] The purpose of travel has been assigned by Google to one of the following categories: retail and recreation, parks, groceries and pharmacies, transit stations, workplaces, and residential. The residential category measures the time users spend at a place labeled as residential. For the other categories Google provides the number of visits at a given place, irrespective of how long any single user spends at the place. Importantly, this categorisation allows us to distinguish between essential and non-essential movement. We deem mobility related to grocery and pharma to be essential travel, while parks as well as retail and recreation-which captures trends for places like restaurants, cafes, shopping centres, theme parks, museums, libraries, and movie theatres-are labelled as non-essential. We exclude the workplace category from our analysis as we are unable to distinguish between movement related to essential jobs and work that can be done from home.

Finally, because Google data are not available for China, information on movement in Chinese cities between January 1, 2020 and May 2, 2020 is taken from Baidu.[31] The variable

[30]In order to comply with privacy regulations, data in a particular place for a particular date might be missing.

[31]The data are downloaded from China Data Lab, 2020, "City Movement Intensity 0101-0502.tab", Baidu Mobility Data, Harvard Dataverse, V16

measures the number of people moving in a given day compared to the average number of people moving in the same day of the previous year.[32]

A.2 Policy

Our main source of data on daily mobility restrictions is the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2020). OxCGRT is a novel dataset which is published by the Blavatnik School of Government at the University of Oxford. It contains various lockdown measures, such as school and workplace closings, travel restrictions, bans on public gatherings, and stay-at-home requirements.[33] Our baseline policy variable is a dummy value taking value 1 if the government either: i) requires not leaving home with exceptions for daily exercise, grocery shopping, and other "essential" trips; or ii) requires not leaving the home with minimal exceptions. Coding our variable this way allows for greater comparability across countries and at different levels of analysis.

We complement OxCGRT data with newly collected information on lockdown orders across US states and Chinese' provinces. For the US, we used online official sources and cross check them with news coverage in the New York Times and a statewide list provided by Littler Mendelson.[34] For China, lockdown dates are collected from Chinese news or Wikipedia. All cities in the Hubei province followed re-opening dates that were clearly stated by the government and reported in the news. However, for cities outside the Hubei province such dates were not always available. In such cases we used the date in which the Chinese transportation ministry announced to restart transportation across China.

A.3 Culture

To examine the role of culture, our main variables are based on the individualism-collectivism measure provided by Hofstede (2001). One advantage with this measure is that it has been

[32]Baidu data are potentially less accurate than mobility data from Google Mobility Report. However, Baidu is the only available source of information on mobility in China.

[33]Data on testing policy and contact tracing are also taken from OxCGRT. See Hale et al. (2020) for more details on the variables available.

[34]https://www.littler.com/publication-press/publication/stay-top-stay-home-list-statewide

widely used and validated in a number of studies.[35] We exploit country-level variation in individualism measures to construct the incidence of individualist cultural traits at the commuting zone-level in the United States (see 4.1).

For robustness, we also construct a measure of attitudes towards obedience and conformity (see Frey et al. (2020)), using data from the World Value Survey (WVS), which is based on face-to-face interviews and uniformly structured questionnaires (Inglehart and et al. (2014)). Since measures of individualism are not available for China, we follow a similar logic and use data on cultural tightness to proxy for obedience and conformity across Chinese provinces (see 5.1). Data on province-level cultural tightness are taken from Chua et al. (2019). The tightness measures at the provincial level are then mapped to Baidu's mobility data at the city-level.

Table A1: Summary statistics.

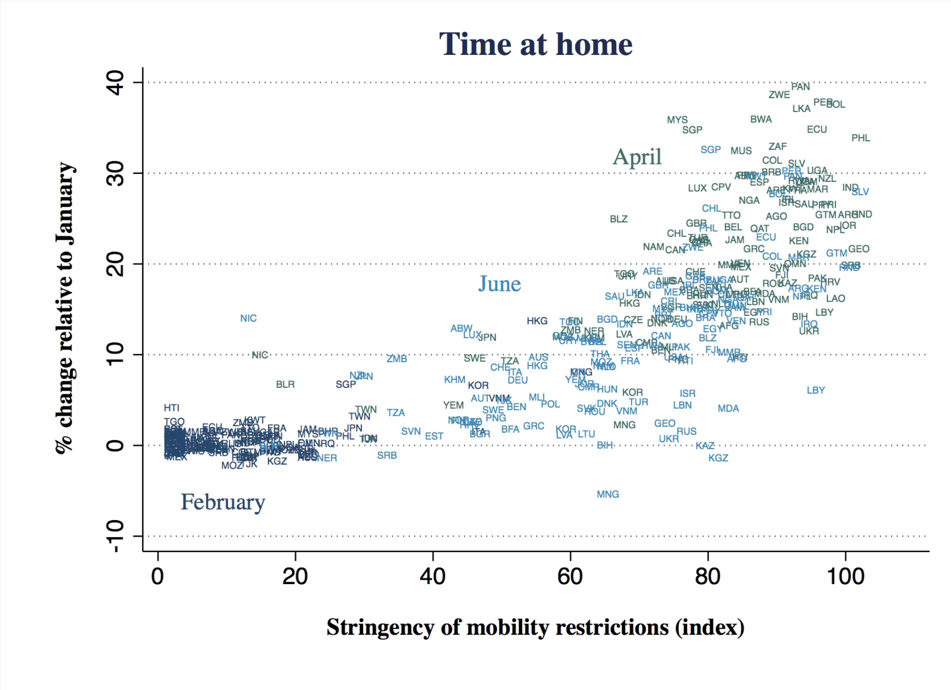
Panel A: Mobility rates	N. of observations	Mean	Std. Dev.	25%	50%	75%
Countries						
Residential	15,853	12.84	10.93	3	12	20
Mobility	80,971	-25.45	30.23	-48	-23	-2
Essential	16,148	-16.24	23.01	-29	-11	1
Non-essential	32,325	-24.38	34.60	-49	-22	-2
United States, counties						
Residential	141,522	9.41	7.73	2	10	15
Mobility	936,899	-10.54	27.30	-29	-10	4
Essential	211,315	1.58	15.32	-7	2	10
Non-essential	299,937	-4.69	36.04	-28	-6	9
China, cities						
Mobility	39,237	80.09	23.27	65.46	87.92	96.57

Panel B: Cultural traits, Policy	N. of observations	Mean	Std. Dev.	25%	50%	75%
Countries						
Individualism (std)	102	0	1	-0.86	-0.40	0.87
Obedience (std)	108	0	1	-0.79	-0.04	0.68
Cellphone subscriptions per 100 people	178	111.10	38.98	89.58	113.14	132.16
GDP per capita ($)	195	15,905.37	23,588.84	2,137.69	6,330.08	19,275.42
Polity revised combined score	166	4.10	6.19	-1	7	9
United States						
Incidence of individualism, CZs (std)	722	0	1	-0.33	0.13	0.69
Incidence of obedience, CZs (std)	722	0	1	-0.55	0.10	0.38
Wage income, CZs ($)	722	23,702.84	5,011.76	20,336.90	22,962.57	26,218.53
China						
Cultural tightness, province (std)	29	0	1	-0.87	-0.16	0.58
GDP per capita, city (rmb)	279	60,926.01	3,4801.03	35,202	50,482	75,987

[35] For an overview, see Gorodnichenko and Roland.

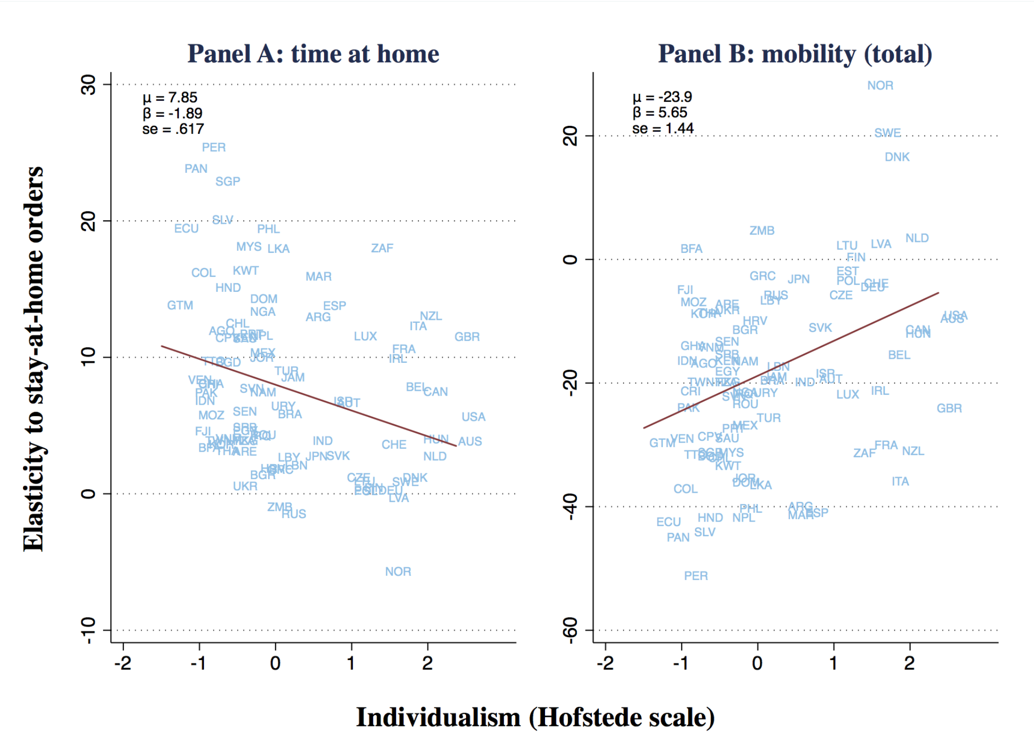
B Figures and Tables Appendix

Figure B1: Lockdown measures and cross-country differences in time spent at home.



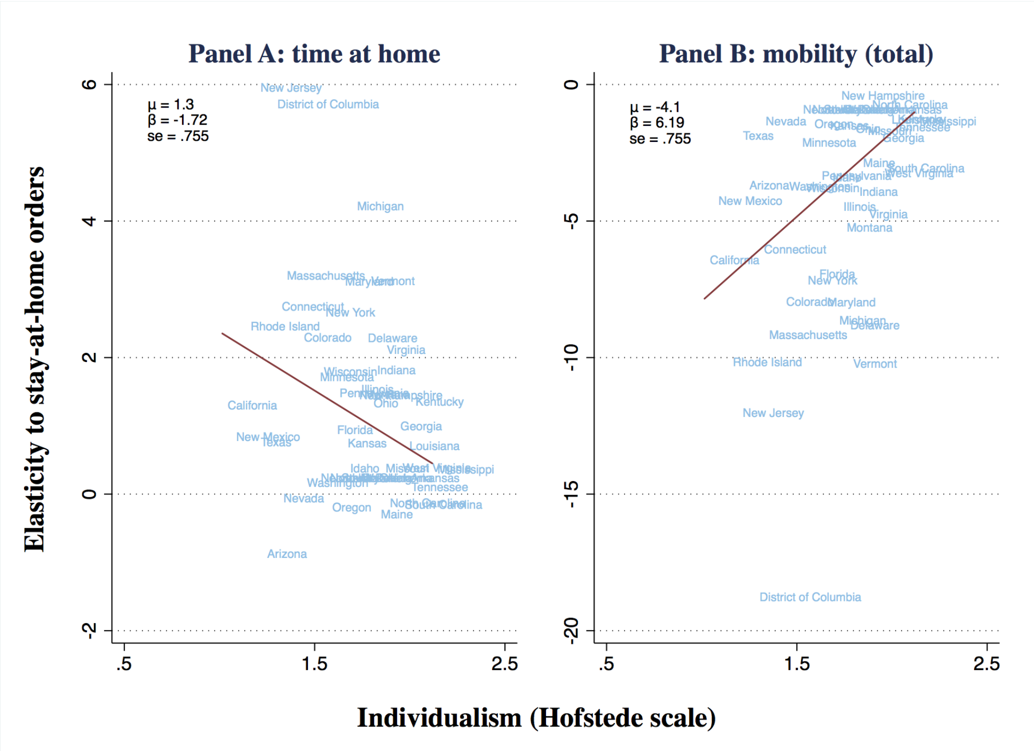
This figure shows the monthly average change in time spent at home on the vertical axis and the policy stringency index on the horizontal axis. See A.1 and A.2 for details on the variables used. Sources: OxCGRT; Google Community Mobility Reports

Figure B2: Individualism and policy compliance across countries.



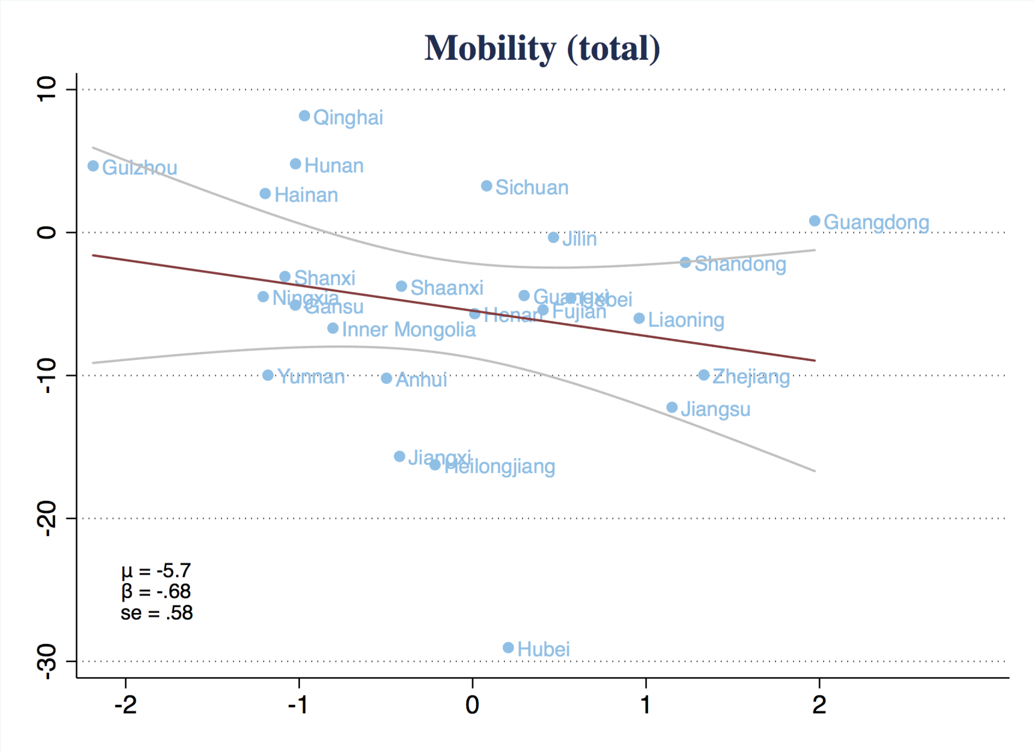
This figure shows individualism measures on the horizontal axis and the estimated elasticities of time spent at home (Panel A) and mobility (Panel B) to stay-at-home requirements on the vertical axis. Each panel reports the average elasticity (μ), the slope of the trend-line (β) and the associated standard errors (se). See 3.1 for details on the underlying econometric specification. Sources: authors' calculations based on OxCGRT, Google Community Mobility Reports and World Value Survey.

Figure B3: Individualism and policy compliance across the United States.



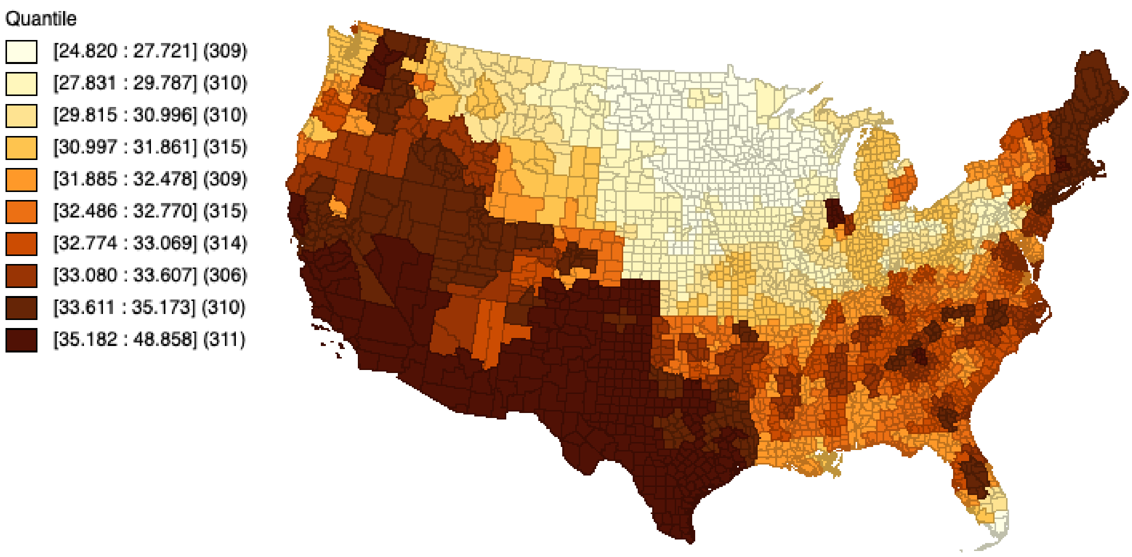
This figure shows individualism measures on the horizontal axis and the estimated elasticities of time spent at home (Panel A) and mobility (Panel B) to stay-at-home requirements. To improve readability, county-level estimated elasticities are averaged by state. Each panel reports the average elasticity (μ), the slope of the trend-line (β) and the associated standard errors (se). See 4.1 for details on the underlying econometric specification. Sources: authors' calculations based on OxCGRT, Google Community Mobility Reports and World Value Survey.

Figure B4: Cultural tightness and policy compliance across China.



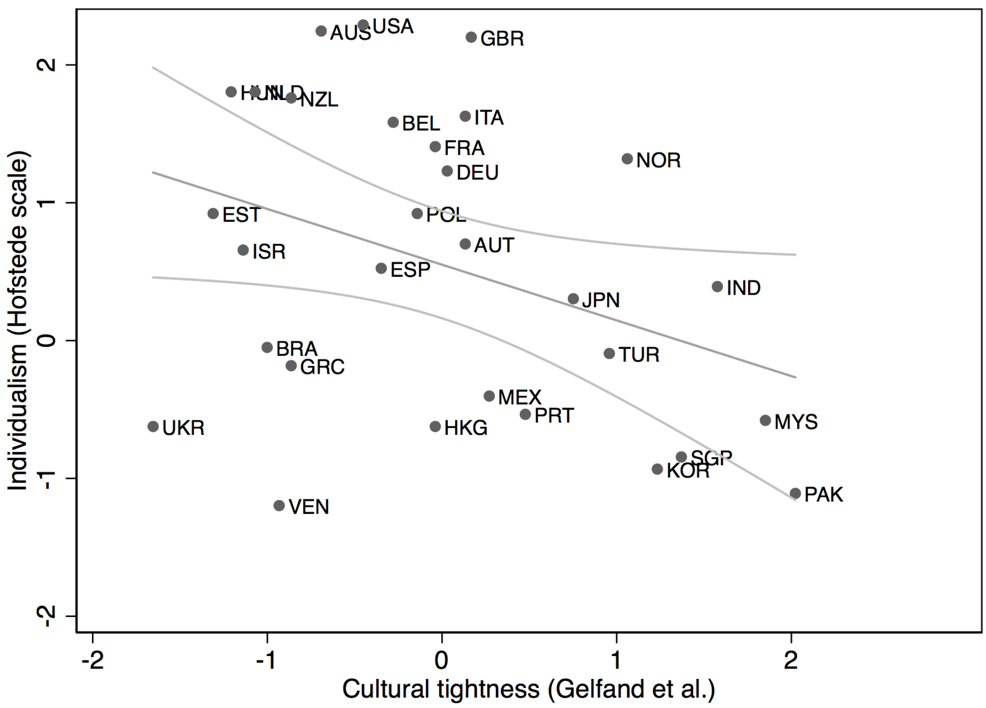
This figure shows tightness measures on the horizontal axis and the estimated elasticities of mobility to stay-at-home requirements. To improve readability, city-level estimated elasticities are averaged by province. It reports the average elasticity (μ), the slope of the trend-line (β) and the associated standard errors (se). See 5.1 for details on the underlying econometric specification, and A.1 and A.2 for details on the variables used. Sources: Baidu; authors' own calculations

Figure B5: Prevalence of obedience across US counties



The figure provides a graphic representation of how each county is positioned in the total distribution of the obedience measure (which varies at the commuting zone-level). Darker shades correspond to a higher incidence of obedience. Sources: authors' own calculations based on WVS; IPUMS USA; David Dorn's data page: https://www.ddorn.net/data.htm.

Figure B6: Individualism and cultural tightness across countries.



This figure shows the cultural tightness measurefrom Gelfand et al. (2011) on the horizontal axis and the individualism measurefrom Hofstede (2001) on the vertical axis. The grey bands around the trend line represent 95% confidence intervals. Sources: authors' own calculations based on Hofstede (2001) and Gelfand et al. (2011).

Table B1: Lockdowns, confirmed COVID-19 cases, and cultural traits across countries.

	(1) Pr(lockdown)	(2) Pr(lockdown)	(3) Pr(lockdown)	(4) Pr(lockdown)
Log-confirmed infections	0.759***	1.249***	0.841***	1.531***
	(0.199)	(0.237)	(0.199)	(0.338)
Log-confirmed infections x individualism	-0.062	-0.029		
	(0.078)	(0.099)		
Log-confirmed infections x obedience			0.045	0.028
			(0.093)	(0.122)
Observations	9,777	8,550	9,939	8,574
Country FE	yes	yes	yes	yes
Date FE	yes	yes	yes	yes
Policy x controls	no	yes	no	yes

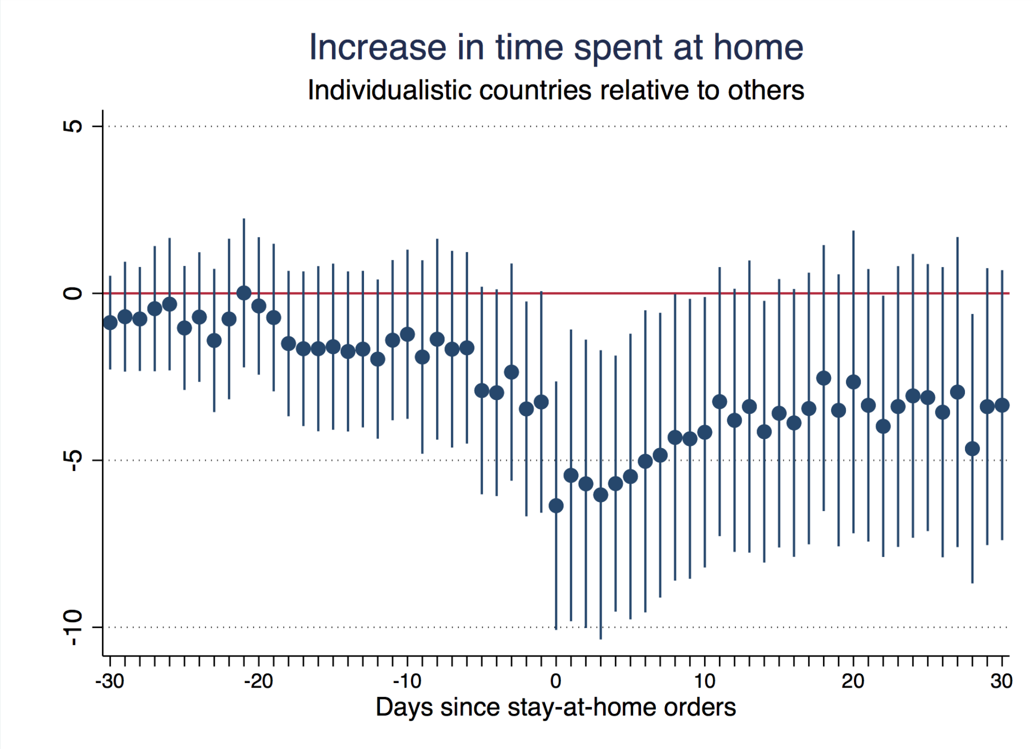
This table presents OLS estimates from regressing a dummy equal to 1 if a stay-at-home order is issued on the log of confirmed infection cases and cultural traits, using a probit model. Columns 2 and 4 include interactions between confirmed cases and: i) the logarithm of real GDP per capita; ii) the number of cellphone subscriptions in the total population; iii) a measure of democracy from Polity Project; and iv) dummy for experience with previous epidemics. The culture variables are normalised to have zero mean and unitary standard deviation. Errors are clustered at the country-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table B2: Individualism and policy compliance across mobility categories and countries.

	(1) Mobility	(2) Mobility	(3) Mobility	(4) Essential	(5) Essential	(6) Essential	(7) Non-essential	(8) Non-essential	(9) Non-essential
Stay at home index	-17.441***	-17.134***	-9.820	-13.232***	-13.211***	-7.333	-19.867***	-20.387***	-9.736
	(1.781)	(2.071)	(7.389)	(1.340)	(1.588)	(5.461)	(2.113)	(2.801)	(9.920)
Stay at home index $\times$ individualism		4.717***	4.410**		3.352***	3.231*		7.434***	7.603***
		(1.423)	(2.208)		(1.096)	(1.680)		(1.918)	(2.781)
Observations	76,711	54,511	45,736	76,646	54,494	45,719	30,686	21,806	18,296
R-squared	0.717	0.718	0.724	0.691	0.694	0.738	0.703	0.708	0.725
Country-mobility category FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Date FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Policy x controls	no	no	yes	no	no	yes	no	no	yes

This table presents OLS estimates from regressing all mobility categories (except residential) (columns 1-3), mobility to grocery shops and pharmacies (columns 4-6), and mobility to parks, retail and entertainment (column 7-9). Country-level mobility is regressed on (the one day-lag of) a dummy taking value 1 if on a given day, the government imposed people to stay at home. Columns 3, 6 and 9 include interactions between the dummy and: i) the logarithm of real GDP per capita; ii) the number of cellphone subscriptions in the total population; iii) a measure of democracy from Polity Project; iv) a dummy for experience with previous epidemics; and v) the log-number of confirmed COVID-19 cases. Errors are clustered at the country-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Figure B7: Estimated coefficients from a country-level event study regression.



This figure shows graphically the estimated coefficients from an event study regression. The horizontal axis represents the days since the implementation of the stay home order across countries. We consider the time span ranging from 30 days before to 30 days after the official implementation of the policy. In the figure, each dot and its 95% confidence interval represent the estimated coefficient of the interaction between the day since policy implementation and a dummy variable equal to 1 if a country is labelled as individualistic. The regression controls for country and date fixed effects, and errors are clustered at the country-level. We define "individualistic" countries as those above the 75th percentile of the sample distribution.

Table B3: Accounting for lead values of the policy variable

	(1) Residential	(2) Residential	(3) Residential	(4) Residential	(5) Residential
Stay at home index	2.694	2.700	2.758	2.828	2.829
	(3.750)	(3.744)	(3.743)	(3.748)	(3.751)
Stay at home index × individualism	-2.254**	-2.294*	-2.202*	-2.201*	-2.232*
	(1.087)	(1.192)	(1.187)	(1.182)	(1.189)
Stay at home index (t+1) × individualism		0.060	-0.177	-0.109	-0.098
		(0.433)	(0.257)	(0.253)	(0.253)
Stay at home index (t+2) × individualism			0.180	0.152	0.312
			(0.455)	(0.297)	(0.254)
Stay at home index (t+3) × individualism				-0.031	-0.055
				(0.414)	(0.335)
Stay at home index (t+4) × individualism					-0.136
					(0.479)
Observations	9,177	9,093	9,008	8,923	8,838
R-squared	0.801	0.801	0.801	0.801	0.802
Country-mobility category FE	yes	yes	yes	yes	yes
Date FE	yes	yes	yes	yes	yes
Policy x controls	yes	yes	yes	yes	yes

This table presents OLS estimates from regressing time spent at home at the country-level on a dummy taking value 1 if on a given day the government imposed stay-at-home restrictions. It includes up to four days lead values of the policy indicator. All columns include interactions between the dummy and: i) the logarithm of real GDP per capita; ii) the number of cellphone subscriptions in the total population; iii) a measure of democracy from Polity Project; iv) a dummy for experience with previous epidemics; and v) the log-number of confirmed COVID-19 cases. Errors are clustered at the country-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table B4: Obedience and policy compliance across countries.

	(1) Residential	(2) Mobility	(3) Essential	(4) Non-essential
Stay at home index	-1.959	0.857	-3.243	3.932
	(3.835)	(8.438)	(8.708)	(10.739)
Stay at home index × obedience	2.999***	-5.808***	-5.178***	-7.253***
	(0.673)	(1.613)	(1.456)	(2.275)
Observations	9,045	45,231	9,043	18,094
R-squared	0.805	0.721	0.629	0.723
Country-mobility category FE	yes	yes	yes	yes
Date FE	yes	yes	yes	yes
Policy x controls	yes	yes	yes	yes

This table presents OLS estimates from regressing time spent at home (columns1) all mobility categories (column 2), mobility to grocery shops and pharmacies (column 3), and mobility to parks, retail and entertainment (column 4) on (the one day-lag of) a dummy taking value 1 if on a given day the government imposed stay-at-home restrictions. All specifications include interactions between the dummy and: i) the logarithm of real GDP per capita; ii) the number of cellphone subscriptions in the total population; iii) a measure of democracy from Polity Project; iv) a dummy for experience with previous epidemics; and v) the log-number of confirmed COVID-19 cases. Errors are clustered at the country-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table B5: Ancestor origin and policy compliance across mobility categories in the United States.

	(1) Mobility	(2) Mobility	(3) Essential	(4) Essential	(5) Non-essential	(6) Non-essential
Stay at home dates (state-level)	-3.055***		-3.360***		-3.192***	
	(0.566)		(0.677)		(0.952)	
Stay at home dates × individualism		1.230***		1.387***		1.523***
		(0.315)		(0.396)		(0.519)
Observations	914,201	914,201	205,548	205,429	291,884	291,884
R-squared	0.674	0.703	0.675	0.768	0.635	0.700
County-mobility category FE	yes	yes	yes	yes	yes	yes
Date FE	yes	yes	yes	yes	yes	yes
State-date FE	no	yes	no	yes	no	yes
Policy x log wages	no	yes	no	yes	no	yes

This table presents OLS estimates from regressing all mobility categories (columns1-2), mobility to grocery shops and pharmacies (column 3-4), and mobility to parks, retail and entertainment (columns 5-6) at the county-level, on (the one day-lag of) a dummy taking value 1 if on a given day the government imposed stay-at-home restrictions. Columns 2, 4 and 6 include interactions between the dummy and the logarithm of wage income per capita and state-date fixed effects. The individualism measure is obtained by summing up country-level measures weighted by the share of ancestors' country of origin. Errors are clustered at the state-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table B6: Birthplace and policy compliance across mobility categories in the United States.

	(1) Residential	(2) Residential	(3) Residential	(4) Residential	(5) Residential
Stay at home dates (state-level)	1.295***	1.033***	0.777***		
	(0.199)	(0.189)	(0.173)		
Stay at home dates $\times$ individualism (birthplace)		-0.759***	-0.233	-0.666***	
		(0.186)	(0.149)	(0.140)	
Stay at home dates $\times$ obedience (birthplace)					0.285*
					(0.151)
Observations	139,009	139,009	139,009	138,847	138,847
R-squared	0.916	0.919	0.922	0.956	0.956
County FE	yes	yes	yes	yes	yes
Date FE	yes	yes	yes	yes	yes
State-date FE	no	no	no	yes	yes
Policy x log wages	no	no	yes	yes	yes

This table presents OLS estimates from regressing time spent at home at the county-level on (the one day-lag of) a dummy taking value 1 if on a given day the government imposed stay-at-home restrictions. Columns 3, 4 and 5 include interactions between the dummy and the logarithm of wage income per capita. Columns 4 and 5 include state-date fixed effects. The individualism measure is obtained by summing up country-level measures weighted by the share of individuals' birthplace. The obedience measure is derived analogously. Errors are clustered at the state-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.