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Francesco Sarracino
STATEC Research a.s.b.l.

Talita Greyling
University of Johannesburg and Auckland University of Technology

Kelsey O'Connor
STATEC Research a.s.b.l., IZA and University of Johannesburg

Chiara Peroni
STATEC Research a.s.b.l.

Stephanie Rossouw
Auckland University of Technology and University of Johannesburg

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Trust Predicts Compliance with COVID-19 Containment Policies: Evidence from Ten Countries Using Big Data*

Previous evidence indicates trust is an important correlate of compliance with COVID-19 containment policies. However, this conclusion hinges on two crucial assumptions: first, that compliance does not change over time, and second, that mobility or self-reported measures are good proxies for compliance. This study is the first to use a time-varying measure of compliance to study the relationship between compliance and trust in others and institutions over the period from March 2020 to January 2021 in ten mostly European countries. We calculate a time-varying measure of compliance as the association between containment policies and people's mobility behavior using data from the Oxford Policy Tracker and Google. Additionally, we develop measures of trust in others and national institutions by applying emotion analysis to Twitter data. We test the predictive role of our trust measures using various panel estimation techniques. Our findings demonstrate that compliance does change over time and that increasing (decreasing) trust in others predicts increasing (decreasing) compliance. This evidence indicates compliance should not be taken for granted, and confirms the importance of cultivating trust in others. Nurturing trust in others, through ad-hoc policies such as community activity programs and urban design to facilitate social interactions, can foster compliance with public policies.

JEL Classification: D91, I18, H12
Keywords: compliance, COVID-19, trust, big data, Twitter

Corresponding author:
Francesco Sarracino
Institut national de la statistique et des études économiques du Grand-Duché du Luxembourg
14, rue Erasme
L-2013
Luxembourg
E-mail: Francesco.Sarracino@statec.etat.lu

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1. Introduction

Governments worldwide implemented public health containment policies such as stay-at-home orders to curb the spread of COVID-19, minimize the loss of life, and take the pressure off the national health systems. Evidence from empirical analysis and mathematical models indicates that measures such as self-isolation, quarantine and social distancing are effective strategies to limit the spread of epidemics (Kucharski et al., 2020; Anderson et al., 2020; O'Connor, 2020b).

However, the effectiveness of public policies to contain epidemics hinges on people's adherence to the prescribed behaviors, i.e. compliance (Brailovskaia and Margraf, 2020). Low compliance rates are undesirable because they can hamper the efficacy of public measures to limit contagion. Additionally, they can lead to increased health care costs because of inefficient and potentially wasteful uses of resources and induce substantial delays in which time viruses can mutate (Kyngäs et al., 2000; Wright et al., 2021; Lewnard and Lo, 2020; Chen et al., 2020). Hence, compliance with health policies is crucial.

In this paper, we use measures of trust in others and in national institutions based on Twitter data to explain national variations of compliance with COVID-19 containment policies over time.

Trust is key to compliance in general. Public policy measures require the cooperation of a large share of the population. They are individually and socially costly, and their psychological toll increases with the stringency and length of containment policies (O'Hara et al., 2020; Kim and Jung, 2021; Zhao et al., 2020). Hence, the incentives for non-compliance are high. Moreover, enforcing containment measures on a recalcitrant population entails high social and economic costs at the expense of people's freedom, confidence in institutions, and sense of social cohesion. But when individuals are more trusting, they are more likely to cooperate, engage in prosocial behavior, and comply with policies (Fukuyama, 1995; Putnam, 2000).

A broad and interdisciplinary literature on compliance indicates that people vary considerably in their willingness to adapt their behaviors to containment measures, such as those to limit the spread of COVID-19 (Levi and Stoker, 2000; Luttmer and Singhal, 2014; Fan et al., 2020). This burgeoning literature primarily focuses on the relationship between compliance with COVID-19 containment measures and trust. These studies mainly use data collected via i) direct observation of behavior / practice, ii) self-reports usually collected through surveys, iii) indirect calculation or iv) survey experiments (see section 2 for full discussion). However, because i) and iv) are not widely available, most studies on compliance and trust use either self-reports or mobility data sourced from Big Data.

The main limitation of these studies, discussed further in section 2, is that the adopted compliance measures are subject to measurement error. Self-reports can be upward or downward biased, depending on the context and respondents, while mobility data provides an accurate picture of people's movements, but movement that is not necessarily linked to containment policies. People may choose to stay home even if it is not mandated by law. The few studies exploiting the association between changes in mobility and changes in policies overcome this problem. However, these studies come at the cost of focusing on a specific point in time, whereas compliance and its correlates may change over time (Bish and Michie, 2010; Williams et al., 2015), especially in the case of long-lasting events.

In this paper, we overcome the limitations of previous studies by developing and analyzing a novel measure of *compliance* varying over time and countries. Our compliance measure does not depend on direct observations, experiments, self-reported compliance, or mobility data alone. We derive our compliance measure from the *association* between mobility behavior and containment policies. In particular, we use a regression of residential mobility on containment policies and interpret the estimated coefficient as the measure of compliance. Residential mobility, or individuals' time spent at home, is obtained from Google Mobility Reports, and we extract the information about containment policies from the Oxford Policy Tracker (see detailed explanation in section 3.1). Using this derived measure of compliance, we can analyze the role of trust in promoting compliance with COVID-19 containment policies across time and countries.

In addition, we use a novel method to construct our trust variables, generalized trust (referred to as trust or trust in others from here on) and trust in institutions, using information sourced from Twitter. Specifically, we extract our text corpus from Twitter and use the NRC lexicon to return the emotion score for 'trust'. We follow the same procedure to construct trust in institutions, but the text corpus is extracted based on tweets containing specific keywords related to institutions. We construct our time series data by averaging the measured value of 'trust' per day per country. The correlation between compliance and trust over time is likely affected by other variables. To limit the effect of confounding factors in our analyses, we use various methods, including dynamic ordinary least squares, fixed effects, instrumental variables, and generalized methods of moments.

We contribute to the literature both methodologically and empirically. Methodologically, we are the first to measure compliance throughout 2020 as the association between containment policy stringency and individuals' time spent at home. Empirically, we use high-frequency daily data to study the relationship between compliance and trust over time, which has not been done before.

Taken together, the results from our models confirm that trust is a robust correlate of compliance within countries over time. This relationship holds after accounting for the role of new confirmed cases. The findings of our two-stages least squares and the Arellano and Bond (1991) dynamic panel approach show that trust positively and significantly contributes to compliance across models. However, the coefficient of trust in national institutions is not statistically significant, though positive. In other words, we provide evidence that trust in others plays an important role in determining compliance with COVID-19 containment policies, followed, to a lesser extent, by the number of new positive cases.

The paper is organized as follows. The next section discusses our conceptual framework regarding trust and compliance. Section 3 introduces our measure of compliance and the additional data used in the study. A discussion of the validity of our measure of compliance is available in Appendix C. Section 4 describes the empirical strategies used to assess the role of trust in determining compliance. Section 5 presents the results of each empirical model and finishes with a brief discussion of the effect size of trust on compliance. Section 6 concludes.

2. Compliance and trust

Compliance and its correlates are the subjects of many disciplines, including medicine, nursing, psychology, and health economics. Therefore, it is unsurprising that there is no commonly accepted definition of compliance (Kyngäs et al., 2000). However, more or less explicitly, most empirical investigations on compliance adopted a cognitive-motivational framework that emphasizes the relationship between attitudes and intentions towards recommended or prescribed healthcare measures (Cameron, 1996). This framework recognizes the importance of individual and social characteristics in shaping people's willingness to comply. Importantly, it clarifies that compliance should not be seen as a duality between compliance and non-compliance. Previous research documents that individuals' perceptions of the costs and risks associated with non-compliance predict their behavior (Bish and Michie, 2010; Williams et al., 2015). These perceptions differ among people and over time, especially as the duration of treatment increases. In the case of COVID-19, containment measures lasted more than one year and compliance with containment measures varied widely across time, countries, the number of fatalities, and the strictness of lockdown measures (Becher et al., 2020; Bargain and Aminjonov, 2020).

In medical disciplines, there are three main methods to measure compliance: direct observation of practice (number of episodes over a number of opportunities); self-reports, i.e., individual's declaration about their own behavior, usually collected through surveys; and indirect calculation based, for instance, on drug consumption (Haas and Larson, 2007). Direct observation is generally regarded as the preferred measure of compliance, as the alternative methods are prone to more errors. For instance, Dresselhaus et al. (2000) administered a survey to analyze the preventive care measures adopted by physicians in their daily routines. The authors found evidence of overshooting;

physicians tend to perform more preventive care initiatives than they declare in medical records. Other scholars cautioned that direct survey questions are likely to suffer from measurement errors due to social desirability bias (Barari et al., 2020; Daoust et al., 2020). This is consistent with the observation that surveys in different countries found high self-reported compliance with recommended health prescriptions (Perrotta et al., 2021; Brouard et al., 2020). Another method is through survey experiments (Becher et al., 2020). This solution consists of administering a list of activities to respondents to see how many tasks the respondent declared to have performed over the previous week. Becher et al. (2020) used survey experiments to examine the prevalence of non-compliance with social distancing in nine countries[1]. The authors split the respondents into two groups, one of which received a list including an item related to violating the social distancing norm (meeting people when not allowed). Results indicate that 25.8% of respondents did not adhere to social distancing guidelines on average. This share is higher than what is computed using estimates based on direct questions from surveys administered in the same countries at approximately the same time (Becher et al., 2020; Perrotta et al., 2021).

Unfortunately, survey experiments and direct measures of compliance are not widely available. This is why the vast majority of studies on compliance with COVID-19 containment measures and its determinants used either self-reported declarations of compliance or mobility data sourced from Big Data, such as cellphone location or Google Mobility Data. Wright et al. (2021) interviewed a longitudinal sample of 51,000 British adults every week for three months of lockdown (1 April to 22 June 2020). Their measure of adherence is based on the following question: "Are you following the recommendations from authorities to prevent the spread of COVID-19?". Respondents could reply using a seven-point Likert scale, where 1 stands for "Not at all" and 7 "Very much so". The availability of repeated, individual-level observations allowed the researchers to account for an exhaustive list of possible correlates. They found that trust in government is the only factor predicting future compliance. In contrast, other factors such as mental health, confidence in the health care system, social experiences and awareness of COVID-19 were not statistically related to future changes in compliance.

There are various reasons to expect that trust, one of the key components of social capital, facilitates compliance. For instance, trust enables the cooperation necessary to achieve common goals, such as limiting the diffusion of a virus (Fukuyama, 1995; Putnam, 2000). Experimental evidence showed that people's propensity to cooperate increases if they expect others to do the same (Fischbacher et al., 2001; Shinada and Yamagishi, 2007). Thus, trust alleviates the incentive to free-ride when i)

[1] Australia, Austria, France, Germany, Italy, New Zealand, Sweden, United Kingdom, and United States.

containment measures are individually costly, and ii) individual behaviour has a negligible impact on containing the virus – a typical social dilemma (Ostrom, 2000). Additionally, available evidence shows trust can change in a relatively short period (Sarracino and Mikucka, 2017; Mikucka et al., 2017). The evidence above suggests these changes can alter the extent to which people choose to comply with containment policies.

Previous research has paid particular attention to the relationship between compliance and trust in others and institutions (Pagliaro et al., 2021; Brodeur et al., 2021; Bargain and Aminjonov, 2020). Chan et al. (2020) show that people in European regions with high confidence in the health care system tend to comply more. Moreover, they find that compliance depends on confidence in government, trust in media and belief in science, moral support, social norms, peer pressure, and a mix of characteristics, including income, risk-taking behavior, personality features, and political orientation. Plohl and Musil (2021) further explored the role of trust in science and COVID-19 risk perception for compliance using a random sample of 525 respondents and structural equation modelling. The authors found that trust in science and risk perception predict compliance. At the same time, the effects of other variables, such as political conservatism, religious orthodoxy, conspiracy ideation, and intellectual curiosity are mediated by trust in science.

Civic capital, which usually correlates with trust, is another important correlate of compliance (Barrios et al., 2021). The authors analyze American individuals, American counties and European regions. Besides showing that civic capital correlates positively with compliance, the authors also found that social distancing was more likely to stay steady in high civic capital counties, even when it was not mandated by law. Durante et al. (2021) reached a similar conclusion using mobility data across Italian provinces in early 2020. The authors found that mobility decreased more in provinces with higher civic capital. Predictions indicate that if all provinces shared the same level of civic capital as the top 25%, mortality in Italy would have been 60% lower (Durante et al., 2021).

Pagliaro et al. (2021) document that people's reported compliance relates positively to various forms of trust (in others, the government and science), but not to the number of infections, using survey data from 23 countries. According to the authors, feelings of fairness and care are at the origin of these relations. This conclusion finds partial support in a study by Nofal et al. (2020) on a sample of about 8,500 Japanese people. The authors observed compliance using a battery of self-reported behaviours in which respondents selected the extent to which they adopted a specific policy (on a scale from 1 to 5, where higher scores indicate more adoption of the behaviour). Results indicate personality traits predict people's compliance. For instance, people high in conscientiousness, openness to experience and agreeableness, which positively correlate with feelings of fairness and care, were more likely to adopt COVID-19 transmission mitigation behavioural guidelines than others. On the contrary, people high in extraversion were less likely to comply. In a longitudinal study on a small sample of U.K. residents, Stevenson et al. (2020) found that community identification, a proxy of the local network of relations and trust, predicted compliance, as measured by the extent to which respondents adhered to COVID-19 containment policies (on a scale from 1 to 5, where higher scores indicate higher compliance).

Additional studies using mobility data support the hypothesis that trust predicts compliance. For instance, Brodeur et al. (2021) merged U.S. cell phone data from Unacast with data on social capital and trust from the General Social Survey (prevalence by county). They found that counties with higher shares of people trusting others showed, on average, a greater decrease in mobility once a containment policy was introduced. Bargain and Aminjonov (2020) reach the same conclusion using Google Mobility Data. The authors use a double-difference approach to estimate the impact of trust (at the regional level in Europe) on decreases in mobility around the time of lockdown: high-trust regions decreased their non-necessary mobility more than low-trust regions.

From the literature discussed, no other study has assessed the role of trust in predicting changes in compliance over time. Previous measures are typically cross-sectional, self-reported or based on mobility data alone. Even when authors utilize time-varying mobility data (not compliance), they lack time-varying measurs of trust. Our time-varying measures of compliance with containment policies, trust in others and in institutions, are comparable across countries, and they derived from high-frequency daily data. Together these measures provide a unique opportunity to study the relationship between trust and compliance over time.

3. Data and variables

3.1. The outcome variable: Compliance

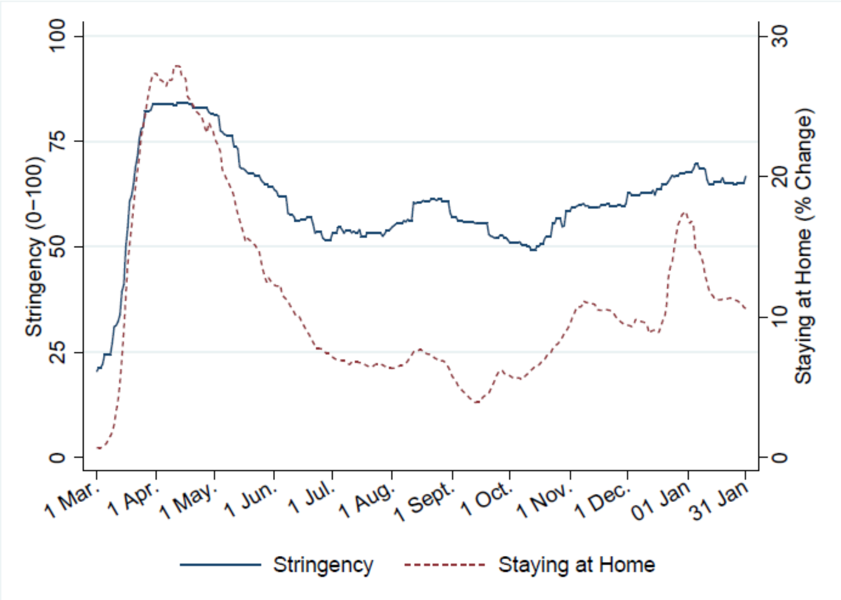
We define compliance as the degree of association between people's behaviours and COVID-19 containment policies. We imagine compliance as a continuum ranging from negative compliance (doing the opposite of what was prescribed) to a perfect one to one association between mandated policies and people's behaviors. In accordance with previous literature, we acknowledge that the degree of compliance changes over time due to changes in its determinants. In particular, we note trust in others and institutions.

We observe compliance at the country level to overcome the measurement limitations of previous studies, which relied mainly on self-reported compliance or changes in mobility (thus observing people's behavior without accounting for the policy). The focus on countries allows us to measure compliance as the association between the stringency of containment policies (left-hand side y-axis of figure 1) and the increase in people's time spent at home (right-hand y-axis of figure 1). The changes of the two variables are fairly consistent over the considered period (from March 2020 to January 2021). For instance, figure 1 shows a sudden increase in stringency and the relative share of people's time spent at home at the beginning of the pandemic (March to May 2020). However, the association between the two measures is not constant over time. The end of December 2020 provides a good example: we observe a much stronger increase in the relative share of people staying at home than in policy stringency. In other words, people stayed at home much more than mandated. In this case, it is clear that the reason is Christmas, but this helps us illustrate the point that compliance changes over time as a consequence of specific conditions.

Data on policies are the Stringency Index provided by Oxford's COVID-19 Government Response Tracker (Hale et al., 2020)[2], whereas information about the time spent at home are sourced from Google Mobility Reports (Google, 2020). Google provides information based on users' location history and indicates daily mobility/visitation to various places by geographic location. We focus on the time spent at home as this variable requires fewer assumptions about people's movements. Data are expressed as the relative number of visits compared to the number of visits during a reference period, i.e. 3 January to 6 February 2020. Data on policy stringency and time spent at home are provided daily throughout the pandemic. Stated intuitively, compliance is the association between the two lines reported in figure 1 (see Appendix A for the average changes of policy stringency and time spent at home by groups of countries).

[2] The Tracker monitors 18 indicators of policy response to the pandemic. The Stringency Index uses the following nine indicators: school closing, workplace closing, cancel events, restriction of gatherings, close public transport, stay at home requirements, restrictions on internal movement, international travel controls, and public information campaigns.

Figure 1: Average policy stringency and time spent at home across countries over time.



Note: Staying at home data are presented using a seven-day (centered) moving average.

Source: Data are sourced from Oxford Policy Tracker (Hale et al., 2020) and Google Mobility Data (Google, 2020).

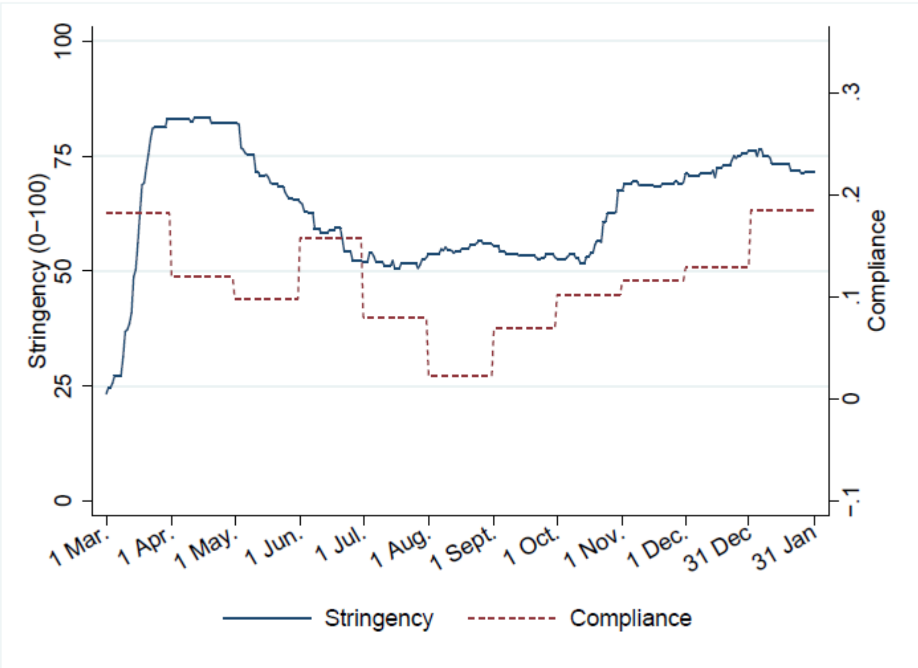
To compute our measure of compliance, we estimate equation (1).

$$res_{ct} = \alpha + \beta_{cm} \cdot Country_c \cdot Month_m \cdot Policy_{ct} + \delta_c Country_c + \lambda_{ws} + \varepsilon_{ct} \quad (1)$$

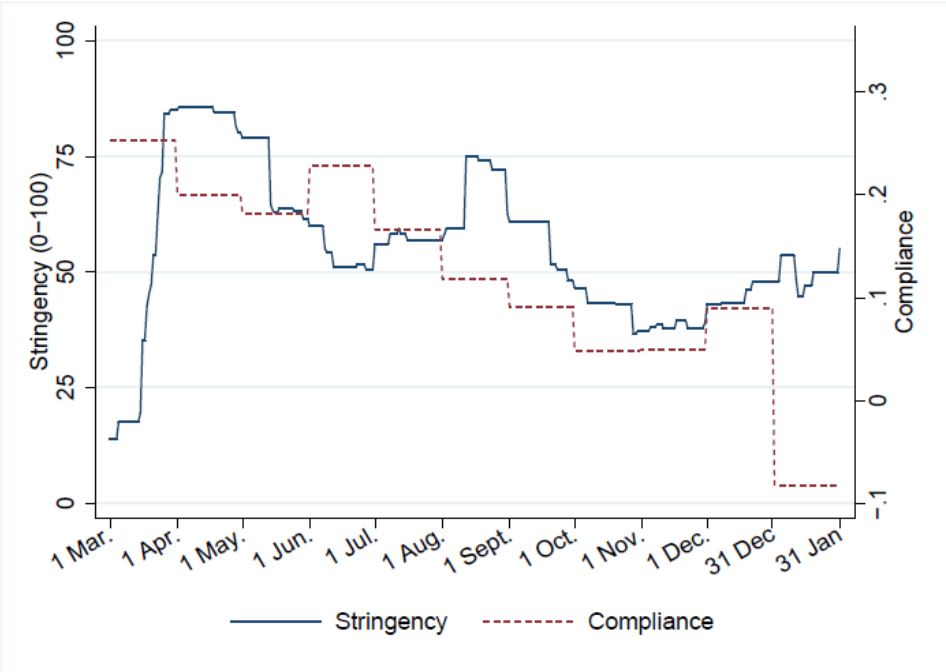
where res_{ct} is residential mobility in country c on day t; $Country$ is a vector of dummies for each country included in the dataset; $Month$ is a vector of dummies for the months m from February 2020 to January 2021. We focus on this period because prior to February 2020, data on mobility are not available, while containment policies started being in place by the end of February; λ_{ws} represents time by hemisphere fixed effects for week w and hemisphere s, to account for the different seasons and evolution of the pandemic among Northern and Southern hemisphere. The coefficient β_{cm} is our compliance measure. It provides the correlation between policy stringency and mobility by country and month. In principle, we could have estimated compliance weekly or daily. However, policy measures do not change frequently enough, and shorter time periods risk introducing noise in our correlation. Appendix C provides evidence supporting the validity of our measure of compliance.

Our measure of compliance is available for nearly every country in the world. However, in the present analysis, we restrict our attention to ten countries, namely Australia, Belgium, France, Germany, Italy, Luxembourg, New Zealand, South Africa, Spain, and United Kingdom. The reason is that our main explanatory variables, trust in others and national institutions, are available only for these countries. Figure 2 shows the average monthly levels of compliance (dashed lines) for European countries in panel 2a and for Australia, New Zealand and South Africa, henceforth A-NZ-SA, in panel 2b. The dashed line for European countries is always positive, indicating a positive association between changes in policy stringency and staying at home (also referred to as distancing). In particular, compliance follows a U-shaped trajectory, which reaches a minimum in August, when policy stringency was at its minimum (excluding the pre-pandemic period). In A-NZ-SA, compliance declines throughout 2020, more so after August, and turns negative after December 2020. This period is characterized by few positive cases and a gradual relaxation of containment measures. However, residential mobility did not closely follow containment policies, as is the case in August 2020 and, in particular, in January 2021. In both months, policy stringency increased, but people did not correspondingly reduce their mobility. We focus on the changes of trust in others and national institutions to explain the differences in compliance across countries and over time. Appendix B provides detailed figures on compliance by country.

Figure 2: Compliance over time in two country groups.



(a) Average compliance in seven European countries



(b) Average compliance in Australia, New Zealand, and South Africa.

Source: Data are sourced from Oxford Policy Tracker (Hale et al., 2020) and Google Mobility Data (Google, 2020).

3.2 Selection of covariates

We derive a number of covariates by extracting tweets and applying emotion analysis to the text corpus. We use the NRC lexicon (National Research Council of Canada Emotion Lexicon developed by Turney and Mohammad (2010)) to code and analyze the underlying tweets' emotions. This is different from sentiment analysis (sentiment given as positive, neutral or negative) and distinguishes between eight basic emotions (Plutchik's (1980) wheel of emotions): joy, surprise, anticipation, trust, sadness, anger, fear and disgust. Emotion analyses have previously been used in a handful of studies (Morrison et al., 2021; Rossouw et al., 2021a; Rossouw et al., 2021b; Greyling et al., 2021a; Luy et al., 2021; Xue et al., 2021).

First, we extract the text corpus of tweets for all countries and derive the underlying emotions. In our study, we focus on the emotions fear, anticipation, and trust. Specifically, the NRC emotion lexicon identifies trust based on how it is commonly used in English. To this purpose, it leverages on a data-base of thousands of people's replies about how specific words evoke trust. Respondents are primed to think about faith and integrity as strongly associated with trust. Each extracted tweet attracts a value for each emotion on a scale from 0 "no fear/anticipation/trust" emotion detected in the tweet to 10 "a high level of fear/anticipation/trust " based on the associations previously identified. We thus regard the resulting trust as a proxy of generalized trust, defined us ``a person's belief that another person or institution will act consistently with their expectations of positive behaviour'' (OECD, 2017b). To derive the time-series data, we average the daily score of the specific emotion per country per day[3]. We also multiply these scores by ten so their scale ranges from 0-100. Available evidence allows us to regard our measures of trust as valid, as they correlate positively and significantly with survey-based measures of trust in others and in national governments (for more details, please, see Appendix D)

Second, we extract tweets based on specific keywords. To construct trust in institutions, we extract a text corpus with only tweets related to institutions[4] and derive the underlying trust of these specific tweets, thus a proxy for trust in institutions. Similarly, we extract keywords[5] related to economic factors and extract the underlying emotion fear as a proxy for economic fear.

Finally, we include the daily number of new positive cases of COVID-19 (new confirmed cases per million in population) to account for the evolution of the pandemic. This variable is extracted from Our World in Data (Roser et al., 2020), and it is transformed using an inverse hyperbolic sine function. This transformation is similar to a logarithmic one, but it is identified for zeros. Table 1 provides summary statistics for the variables included in our study.

[3] For more details about the construction of this variable, please, see Greyling et al. (2021b); Sarracino et al. (2021).

[4] The keywords used are government, parliament, ministry, minister, senator, MPs, legislator, political, politics, prime minister.

[5] The list of keywords includes jobs, economy, saving, work, wages, income, inflation, stock market, investment, unemployment, unemployed, employment rate, tech start-up, venture capital.

Table 1: Descriptive statistics. Average monthly values.

Variable	Obs	Mean	Std. Dev.	Min	Max
Compliance	100	0.108	0.082	-0.209	0.328
Residential mobility	100	11.232	7.142	0.645	33.067
Stringency	100	62.106	16.542	22.220	95.127
IHS New Cases	100	4.112	2.094	0.165	7.533
Lag Trust	90	6.658	0.822	5.560	9.023
Lag Nat. Trust	81	8.917	1.837	6.769	12.068
Lag GNH	90	6.999	0.426	5.992	7.640
Lag Anticipation	90	5.921	0.722	4.917	7.559
Lag Fear	90	3.620	0.526	2.927	5.090
Lag Economic Fear	81	4.073	1.090	2.803	6.273

Note: Monthly Data April 2020 - Jan. 2021. Compliance begins in March, the first month for which mobility data cover the whole month, and March is dropped to include lags. Due to data limitations, fewer observations are available for national trust and economic fear because they could not be collected for Luxembourg.

Source: all sources are described in the text. They are omitted for brevity.

4. Methodology

The correlation between compliance and trust over time is likely affected by other variables, such as the severity of the pandemic, economic situation, weather conditions, or seasons. To account for the possible confounding effects of these variables, we resort to various econometric techniques.

In principle, we would like to estimate the following equation:

$$Compl_{cm} = \alpha + pCompl_{cm-1} + \beta Trust_{cm-1} + \delta IHS(newcases)_{cm} + \lambda_m + \mu_c + \varepsilon_{cm} \qquad (2)$$

where $Compl_{cm}$ is compliance as defined in the data section for country c in month m; $Trust_{cm-1}$ is the average level of trust for country c in the month $m-1$. $IHS(newcases)_{cm}$ is the transformed number of new daily cases per one million residents (on average over the month) in country c. λ_m are month effects, while μ_c are country effects. Additional controls are added in robustness tests, discussed below.

This specification addresses many potential sources of bias. Reverse causality is reduced by lagging trust and including lagged compliance as a control. Omitted variables are addressed in part by including fixed effects (FE), which account for all fixed characteristics, both observed and unobserved.

Lagged compliance likewise captures anything that affects both current and lagged compliance, both observed and unobserved. Current cases capture the country-specific time-varying evolution of the pandemic. Cases in the current period, one period after lagged trust, also capture people's expectations of the pandemic in their country. Common effects across countries, such as seasonal effects and global trends in the pandemic, are captured using month controls. However, this equation cannot be estimated by ordinary least squares (OLS) without bias. Nickell Bias (Nickell, 1981) arises when including both lagged compliance and FE[6].

4.1 Dynamic OLS and Fixed Effects

Equation (2) can be estimated when excluding either the FE or lagged compliance. For this reason, we use FE estimation when excluding lagged compliance and dynamic OLS (DOLS) when including lagged compliance but excluding the FE[7]. Estimates from the two methods should also bound the true estimate (Angrist and Pischke, 2008: pp. 184)[8].

4.2 Instrumental Variable approach

Under certain conditions, it is possible to use an alternative approach to account for both FE and DOLS (Anderson and Hsiao, 1981). The authors apply first differences to equation (2) to account for FE. First differences, however, cause the lagged differenced dependent variable to be related to the differenced error term. To overcome this problem, lagged differenced compliance is predicted in a first stage and then used in a two-stage instrumental variable (IV) approach. Equation (3) presents the second-stage specification:

$$\Delta Compl_{cm} = p\Delta \widehat{Compl}_{cm-1} + \beta \Delta \widehat{Trust}_{cm-1} + \delta \Delta IHS(\widehat{newcases})_{cm} + \Delta\lambda_m + \Delta\varepsilon_{cm} \quad (3)$$

Where $\Delta Compl_{cm} = Compl_{cm} - Compl_{cm-1}$ and $\Delta \widehat{Compl}_{cm-1}$ is the predicted value for $\Delta Compl_{cm-1}$. Anderson and Hsiao (1981) suggest $Compl_{cm-2}$ as a valid instrument for $\Delta Compl_{cm-1}$. $Compl_{cm-2}$ is relevant because it is correlated with $\Delta Compl_{cm-1}$ and it is excludable (not correlated with $\Delta\varepsilon_{cm}$) if there is no autocorrelation in the level equation 2 (i.e., $cov(\varepsilon_{cm,}\varepsilon_{cm-1}) = 0$).

[6] Fixed-effects models are typically estimated by subtracting from each variable its mean value over time, and in the case of a dynamic panel, the mean of the lagged dependent variable is correlated with the mean error term. In other words, de-meaning introduces a source of endogeneity.
[7] Similar approaches were used in (Flèche and Layard, 2017; Krekel et al., 2020; O'Connor, 2020a).
[8] If fixed effects represent the true data generating process, but a dynamic model is used, then the resulting estimate will be biased downward. However, if the true data generating process is dynamic but fixed effects are used, then the estimate will be biased upward.

$\Delta Trust_{cm-1}$ and $\Delta IHS(new\ cases)_{cm}$ are also allowed to be endogenous and predicted in the same way. We extended this approach by including the additional instruments: $\Delta Compl_{cm-2}$, $\Delta Trust_{cm-2}$, and $\Delta IHS(new\ cases)_{cm-1}$ to improve the first stage predictions.

This IV approach has limitations. The assumption is that there is no autocorrelation in the level equation, but we know there is serial correlation in each of the variables: compliance, trust, and new cases. Typically, an overidentification test would be used to assess whether the instruments are excludable, but in this case, we have too few clusters for the Hansen test. For this reason, we do not emphasize the IV results alone.

4.3 Arellano and Bond

A different approach builds on Anderson and Hsiao's work, described by Arellano and Bond (1991). Arellano and Bond recognized that further lags could be used as additional instruments. For example, both $Compl_{c1}$ and $Compl_{c2}$ are valid instruments for $\Delta Compl_{c3}$. For $\Delta Compl_{c4}$ even more instruments are available, specifically: $Compl_{c1}$, $Compl_{c2}$, and $Compl_{c3}$. In this way, an additional instrument is added for each period. Estimation of this structure is then performed using generalized methods of moments (see Arellano and Bond, 1991, for more details). The method proposed by Arellano and Bond has the same limitations as the method proposed by Anderson and Hsiao but improves efficiency with the additional instruments. To test for instrument validity, one assesses the degree of autocorrelation in the predicted residuals. It is expected that there is first-order autocorrelation in the predicted residuals from equation (3) due to the mechanical relation between $\Delta Compl_{it-1}$ and $\Delta Compl_{it-2}$ but there should be no second-order autocorrelation for the instruments to be valid. A further limitation of the approach is that the results are often unstable in small samples. In any case, we also include an Arellano and Bond estimation as a robustness test.

4.4 Statistical significance

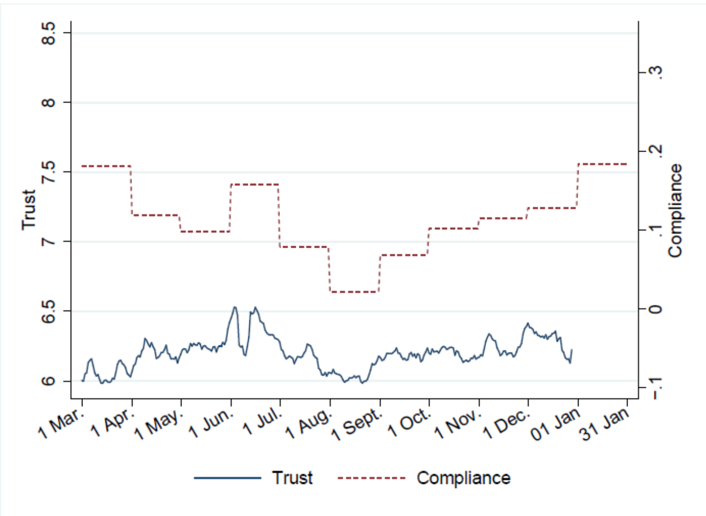
We assess statistical significance using Wild Cluster Bootstrap methods (using 999 replications). Clustering standard errors at the country level is necessary to allow for serial correlation within countries. Bootstrap methods are necessary because a small number of clusters leads to rejecting the null hypothesis relatively more frequently, in some cases at more than double the critical value (Bertrand et al., 2004). The limitation of Wild Cluster Bootstrap methods is that only p-values from the bootstrap distribution can be obtained. Standard errors cannot be estimated using this method because it includes asymptotic refinement (sample estimates approach the population values at a faster rate), which can only be performed on statistics that do not depend on unknown parameters. For this reason, the bootstrapped p-values are reported in the tables. For a further explanation of Wild

Cluster Bootstrap methods, see Cameron and Miller (2015); when using IV, see Davidson and MacKinnon (2010); and for implementation using STATA, see Roodman et al. (2019).

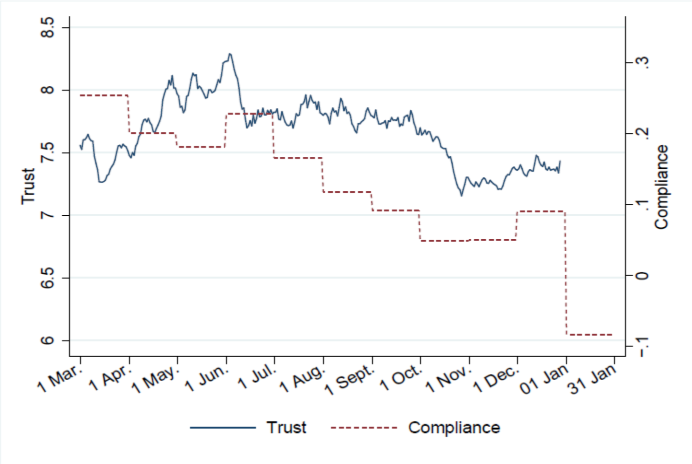
5. Results

Figure 3 shows the changes in trust and compliance over time in Europe (panel 3a) and A-NZ-SA (panel 3b). Compliance follows a U-shaped pattern in Europe which is partly matched by the changes in trust. The first three months of the pandemic are characterized by declining compliance and rising trust in others. In June, trust reaches a peak, and from that moment onward, the changes in trust accompany compliance rather well. Compliance declines from March 2020 to January 2021 in A-NZ-SA. In this case, the association with trust is unclear. However, many factors may confound the association between our two measures. We turn to our regression analysis in an attempt to single out the net effect of trust on compliance.

Figure 3: Compliance and trust across countries.



(a) Average compliance in seven European countries.



(b) Average compliance in Australia, New Zealand, and South Africa.

Note: Trust data are presented using a seven-day (centered) moving average.

Source: Data are sourced from Oxford Policy Tracker (Hale et al., 2020) and Google Mobility Data (Google, 2020).

Table 2 shows the results of our baseline model. The first column shows the results of the most basic model in which compliance is regressed over the number of new positive cases of COVID-19, and the lagged value for trust ($(month_{m-1})$. We find positive and statistically significant coefficients for both variables: the higher the number of new positive cases, and the higher the lagged trust, the higher is compliance. The positive association between new cases and compliance suggests that the more severe people perceive the pandemic, the more they tend to follow the required behaviors. This result is based on the analysis of ten countries over a period of ten months, for a total of a hundred observations. The adjusted R-squared is 0.29, indicating that a large part of the total variance remains unexplained.

In columns 2 to 7, we run the DOLS and FE model separately for trust and trust in institutions. The inclusion of trust in institutions reduces the number of observations to 90 because data for Luxembourg are not available. Despite this decrease, the results qualitatively change very little. The trust coefficient is positive but not statistically significant in the DOLS models. In the FE models, the trust coefficient is positive, large and statistically significant. The larger coefficients in each of the FE regressions are consistent with expectations, according to which the true effect of trust should lie between the DOLS and FE estimates (see footnote 6). The coefficient of trust in institutions is small and largely not significant; it turns negative in the models with FE. The coefficient of lagged compliance is large, positive, and statistically significant. The DOLS models explain the largest share of the total variance (about 67%), though R-squareds from DOLS and FE models are not very comparable. FE models are generally estimated using a within transformation, which reduces the variation in the dependent variable.

The last two models (columns 8 and 9) include at the same time trust and trust in institutions. The latter attracts a negative but statistically insignificant coefficient. In contrast, lagged trust, lagged compliance, and new cases attract positive and statistically significant coefficients in both the DOLS and FE models (except new cases in the fixed effect model).

Table 2: Baseline regression results on the association between correlation and trust in others and national institutions. Results are from OLS, DOLS and OLS with FE.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	DOLS	FE	DOLS	FE	DOLS	FE	DOLS	FE
Lag Trust	0.055	0.013	0.115			0.014	0.175	0.026	0.201
	[0.088]	[0.220]	[0.039]			[0.246]	[0.006]	[0.062]	[0.007]
Lag Nat. Trust				0.001	-0.013			-0.007	-0.053
				[0.840]	[0.483]			[0.141]	[0.127]
Lag Compliance		0.795		0.841		0.797		0.798	
		[0.000]		[0.001]		[0.000]		[0.000]	
IHS New Cases	0.029	0.014	0.017	0.012	0.027	0.016	0.016	0.015	0.018
	[0.016]	[0.009]	[0.201]	[0.013]	[0.056]	[0.017]	[0.298]	[0.005]	[0.237]
Constant	-0.398	-0.172	-0.761	-0.089	0.098	-0.184	-1.154	-0.205	-0.878
N	100	100	100	90	90	90	90	90	90
# Of Countries	10	10	10	9	9	9	9	9	9
Adj. R Sq.	0.294	0.658	0.38	0.662	0.252	0.67	0.424	0.671	0.454
Bootstrapped p-values in brackets									

Note: Dummy variables for months are included but omitted for brevity. P values are shown in brackets

Source: Authors' own computation.

This evidence confirms that trust correlates with compliance over time above and beyond the effect of new positive cases, previous compliance, or country fixed effects. However, this does not completely exclude the hypothesis of a spurious relationship driven by a third (time-changing) variable. To address this issue, we run an additional set of DOLS and FE to check the robustness of our finding to the inclusion of controls for economic fear, anticipation and fear (each lagged by one month). Previous results do not change significantly. As reported in table 3, trust retains its positive and statistically significant coefficient in most specifications, as well as lagged compliance and new positive cases (not significant in the case of FE models). In addition, we find that the experience of fear or economic fear in the previous month tend to reduce compliance in the DOLS models, whereas lagged anticipation does not attract a statistically significant coefficient.

Table 3: Dynamic and fixed effects models with additional control variables.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	DOLS	FE	DOLS	FE	DOLS	FE
Lag Trust	0.032	0.174	0.018	0.193	0.024	0.073
	[0.004]	[0.006]	[0.350]	[0.053]	[0.003]	[0.040]
Lag Economic Fear	-0.017	0.004				
	[0.003]	[0.877]				
Lag Anticipation			-0.006	-0.124		
			[0.679]	[0.177]		
Lag Fear					-0.026	0.079
					[0.020]	[0.159]
Lag Compliance	0.805		0.783		0.836	
	[0.000]		[0.000]		[0.000]	
IHS New Cases	0.015	0.015	0.014	0.014	0.013	0.017
	[0.008]	[0.387]	[0.010]	[0.339]	[0.023]	[0.215]
Constant	-0.236	-1.16	-0.167	-0.534	-0.152	-0.771
N	90	90	100	100	100	100
# of Countries	9	9	10	10	10	10
Adj. R Sq.	0.675	0.417	0.655	0.404	0.66	0.4
Bootstrapped p-values in brackets						

Note: Dummy variables for months are included but omitted for brevity.

Source: Authors' own computation.

The joint reading of the results from DOLS and FE provides evidence supporting the hypothesis that trust predicts compliance across countries and over time. To check the robustness of our findings, we run an additional model that allows for DOLS and FE, i.e., we use the Two-Stage Least Squares (2SLS) IV approach described in section 4 (see Table 4).

Table 4: Two-stages least squares and Arellano & Bond estimates to account for endogeneity in lagged differenced compliance.

Variable	(1)	(2)	(3)	(4)	(5)
	First Stage	First Stage	First Stage	2SLS	A&B
	$Lag\Delta Compl$	$Lag\Delta Compl$	$\Delta Cases$	$\Delta Compl$	$\Delta Compl$
$Lag2\ Compliance$	-0.337	0.187	1.275		
	(0.05)	(0.365)	(1.172)		
$Lag\ 2\ \Delta Compl$	-0.13	-0.966	-2.184		
	(0.084)	(0.97)	(1.665)		
$Lag2\ Trust$	0.021	-0.114	-0.651		
	(0.008)	(0.074)	(0.095)		
$Lag2\ \Delta Trust$	-0.005	-0.215	-0.409		
	(0.006)	(0.102)	(0.245)		
$Lag\ IHS(newcases)$	0.014	-0.013	-0.289		
	(0.003)	(0.022)	(0.021)		
$Lag\ \Delta IHS(newcases)$	-0.002	-0.006	0.556		
	(0.003)	(0.025)	(0.096)		
$Lag\ \Delta Compl$				0.621	0.625
				(0.22)	(0.1)
$Lag\ \Delta Trust$				0.149	0.062
				(0.037)	(0.026)
$\Delta IHS(newcases)$				-0.03	0.015
				(0.018)	(0.004)
Constant	-0.17	0.777	5.561	0.026	
	(0.064)	(0.523)	(0.65)	(0.011)	
N	80	80	80	80	80
# of Countries	10	10	10	10	
Adj. R Sq.	0.627	0.086	0.377	-0.391	
Kleib. F Stat				6.587	
AR1p					0.015
AR2p					0.112
Clustered standard errors in parentheses					

Note: Dummy variables for months are included but omitted for brevity.

Source: Authors' own computation.

Presented in Table 4, columns 4 and 5, trust continues to attract a positive and statistically significant coefficient independently from the chosen model. As expected, the magnitude of the A&B coefficient is between the lower and upper boundaries set by the coefficients of the DOLS and FE (see columns 2 and 3 of Table 2), and the 2SLS coefficient is near the upper bound.

The first three columns of Table 4 show the first stage results, column 4 reports the second-stage (2SLS) results, and column 5 shows the results using the alternative technique provided by Arellano and Bond (A&B)(1991). The number of observations is 80 because we use twice lagged values of the independent variables to predict the lagged, differenced endogenous variables. 2SLS and A&B provide fairly consistent results. Lagged differenced compliance remains statistically significant in both specifications. New positive cases remain statistically significant, but the sign changes depending on the regression method used (negative in case of 2SLS, positive otherwise).

Collectively, the models give us some hint at the true effect size. The point estimates from the DOLS and FE are 0.013 and 0.115 (Table 2, cols. 2 and 3), while the point etimates from the 2SLS and AB models are 0.149 and 0.062 (Table 4, cols. 4 and 5). The first two estimates should bound the true effect, as mentioned above, while the second two are unbiased if correctly specified. This leads us to conclude on an effect size of 0.060, which is not insubstantial. A one standard deviation increase (0.81) in trust is associated with a 0.05 increase in compliance (0.05 = 0.81*0.06), which is 0.6 of a standard deviation in compliance (0.08), or 22 minutes on average across the whole population. 22 minutes is obtained in a couple steps: first, by multiplying the increase in compliance by the mean level of stringency 0.05* 62.1, which yields 3.05 percent more time at home; second, 3.05 is multiplied by the (unknown) baseline time spent at home, which we assume is 12 hours. The result is 0.03*12 = 0.37 hours or 22 minutes.

In sum, various regression methods and specifications provide evidence supporting the hypothesis that trust is an important, if not the single most important, predictor of changing compliance over time.

6. Conclusions

This is the first study that derived a time-varying measure of compliance (the association between time-at-home and the Stringency Index) to investigate the relationship between compliance and trust for ten countries spanning the period from March 2020 to the end of January 2021. Additionally, our study is the first that used tweets extracted from Twitter and emotion analyses to construct high-frequency daily data to measure trust, fear, anticipation, trust in institutions, and economic fear. To construct the variables 'trust in institutions' and 'economic fear', we extracted tweets containing specific keywords representing institutions and the economy, respectively, which has not been done before. The abovementioned allowed us to contribute both methodologically and empirically to the literature.

We used dynamic ordinary least squares and fixed effects panel regressions in our primary analysis to analyze the relationship between trust and compliance over time and across countries.

Our results indicate that trust is a robust correlate of compliance over time and across countries. This relationship also held after accounting for the role of new positive cases. We further verified our findings' robustness using two-stage least squares and the Arellano and Bond dynamic panel approach. Both techniques allowed us to account for the endogeneity in lagged compliance, trust, and new cases. We find trust positively and significantly contributes to compliance across models. However, the coefficient of trust in national institutions is not statistically significant. In other words, we find, relationships among people (generalized trust) seem to play a major role in compliance followed, to a lesser extent, by the number of new positive cases.

Our findings suggest that promoting trust in others would facilitate compliance with public policies to combat epidemic outbreaks. The literature provides various examples for decision makers to promote trust in others (Lund, 2003; Montgomery, 2013). For instance, enhancing the degree of neighborhoods' walkability facilitates social interactions and fosters the sense of community (Alesina and La Ferrara, 2002; Du Toit et al., 2007; Frank et al., 2010). Such policies do not have to be expensive: even dog walking would facilitate social interactions and strengthen a community's social fabric (Wood and Christian, 2011). In general, promoting good quality public spaces, pedestrian areas, parks, and public transport where people can meet and socialize could lead to a greater sense of collective responsibility, trust in others, and increase individuals' willingness to comply in order to protect others.

We note that even though trust in institutions is not significant, it is positively related to compliance in the fixed effects panel estimations. Therefore, we believe that any steps taken by policymakers to increase trust in institutions can increase general trust in communities. This includes transparency in decision making and reducing corrupton.

Our study confirms the results of previous studies while overcoming some of their limitations. However, our study is not free from limitations. The small number of countries and short period reduces the number of observations, which reduces statistical power and the possible set of control variables. Nonetheless, we feel that our specifications account for many possible sources of bias. Our approach focuses on countries and does not allow us to study heterogeneity within countries. Finally, emotion analysis applied to Twitter data is likely susceptible to the number of Twitter users in a country. For instance, in small countries, such as Luxembourg, emotions linked to specific keywords do not provide enough Tweets to derive reliable information.

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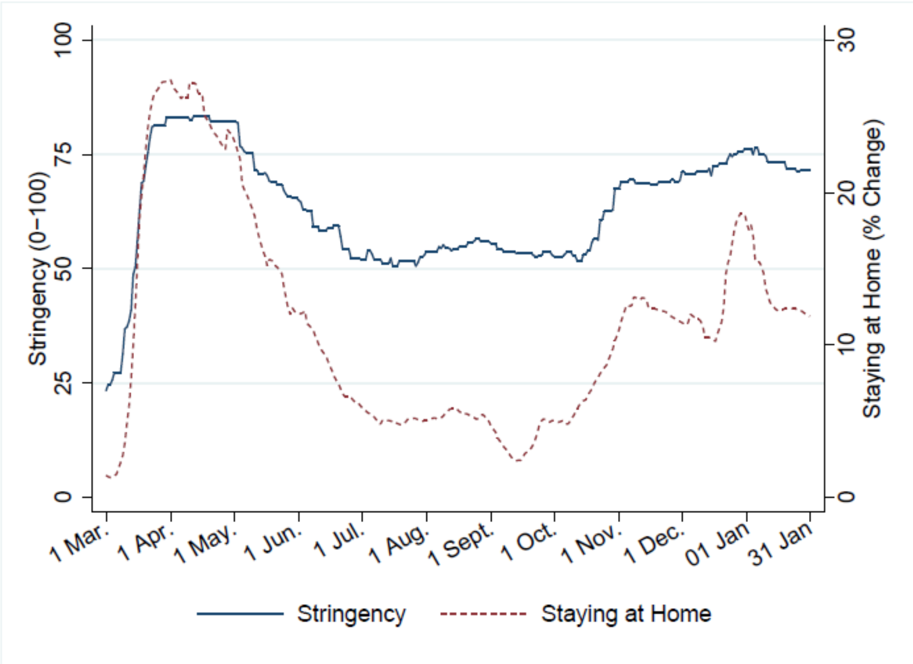
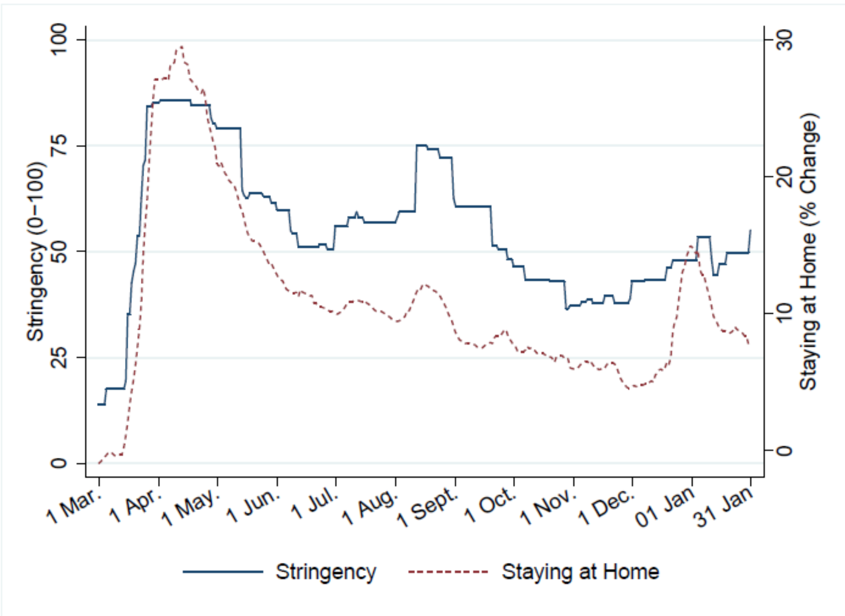
Appendix A: Policy stringency and time spent at home.

Figure A1: Average changes of policy stringency and time spent at home by groups of countries.



(a) Average changes in seven European countries.



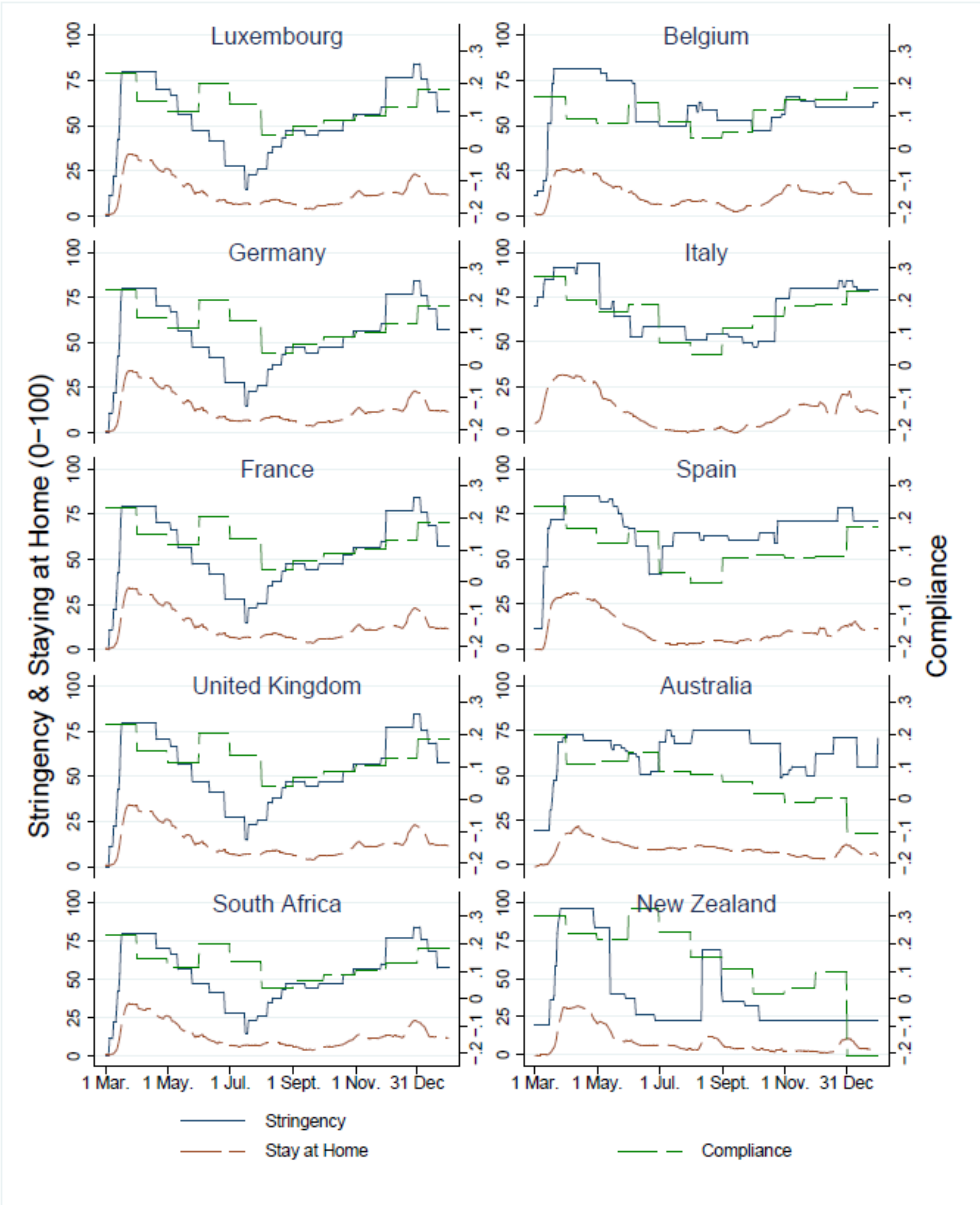
(b) Average changes in Australia, New Zealand, and South Africa.

Note: Staying at home data are presented using a seven-day (centered) moving average.

Source: Data are sourced from Oxford Policy Tracker (Hale et al., 2020) and Google Mobility Data (Google, 2020).

Appendix B: Compliance by country.

Figure B1: Compliance and its two components by country over time.



Note: compliance is the association between policy stringency and time spent at home. It is computed following equation 1. The structure of equation 1 and need to omit one country-month to avoid collinearity, means compliance is measured relative to the omitted country-month, which is Luxembourg in Feburary. This choice affected the absolute level of compliance, but does not affect the variation across country and over time within country.

Source: Data are sourced from Oxford Policy Tracker (Hale et al., 2020) and Google Mobility Data (Google, 2020).

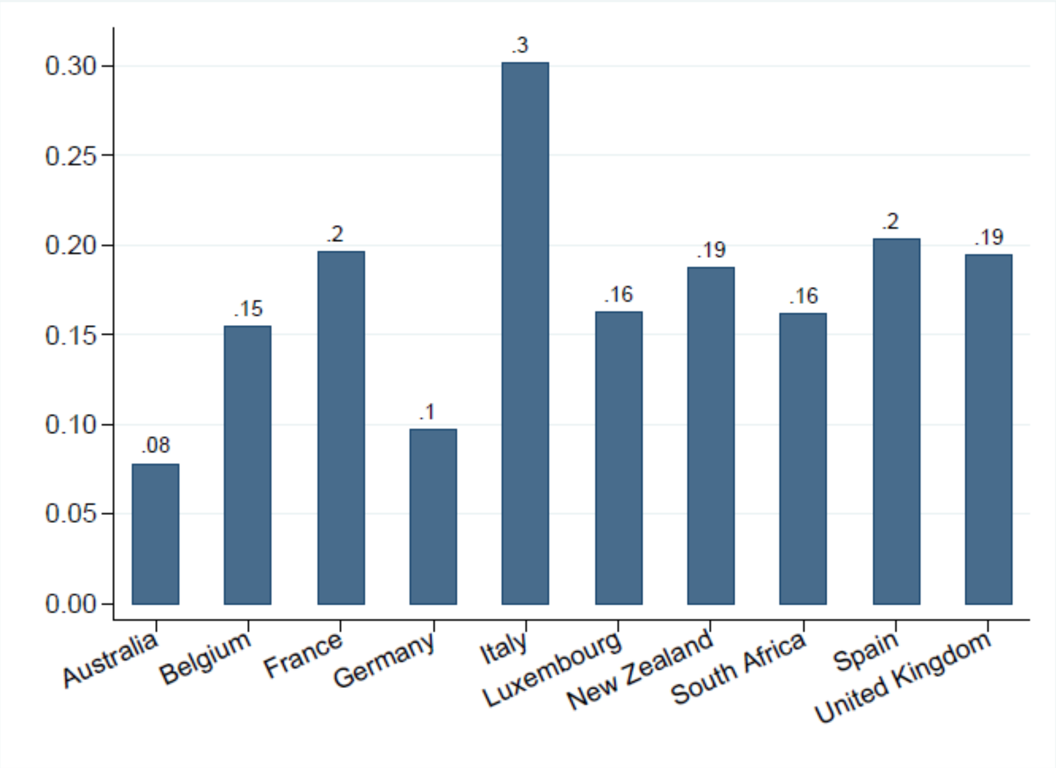
Appendix C: Validity of compliance.

As far as we know, this is the first study that conceptualizes compliance as the association between policy and behaviors using Big Data. Therefore, it is reasonable to question the validity of our measure to ensure its ability to correctly measure the extent to which people abide by the rules.

A major difficulty in assessing compliance's validity is finding a suitable yardstick. Unfortunately, other measures of compliance based on the association between policy and behaviors over time are not available. Therefore, we compare yearly compliance with data provided by other sources.

Figure C1 shows the average yearly compliance computed using our data. For instance, if containment policies become more stringent by ten points (0- 100), Italians' time spent at home increases by 3 per cent. Assuming base time at home is 12 hours, 0.03*12 = 0.36 hours = 21.6 minutes. Stringency went from 0 to more than 80, which would lead to an 80*0.3 = 24 per cent increase in time spent at home. On 12 hours, that's 0.24*12 = 2.88 hours, on average.

Figure C1: Compliance across countries.



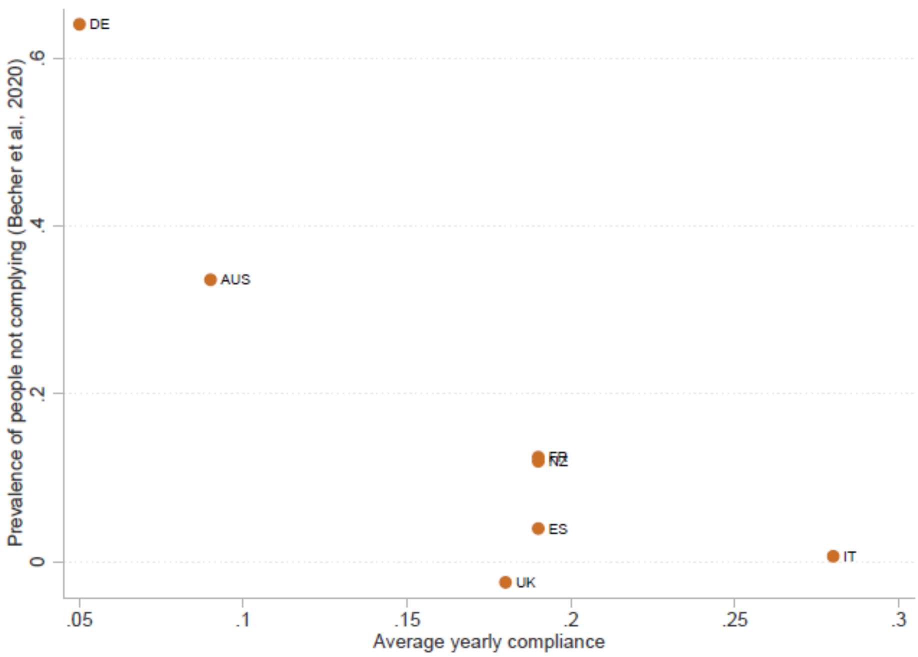
Note: the average country levels of compliance are computed using a modified version of equation (1) whereby the β coefficient is estimated by country without the interaction by month. In the modified version of equation 1, it was not necessary to omit a country month – meaning compliance is estimated accurately in levels, it is not relative to an omitted category.

Source: Data are sourced from Oxford Policy Tracker (Hale et al., 2020) and Google Mobility Data (Google, 2020).

An external source of reliable data on compliance is provided for nine countries by Becher et al. (2020). The authors used experimental evidence to infer information about people's *non-compliance* to social distancing guidelines during the COVID-19 pandemic. We computed the correlation between our measure of compliance. The two measures should be negatively related to each other. The result is reported in Figure C2. The two datasets have only six countries in common, and the Pearson's correlation coefficient is -0.88 (significant at 5%, with N = 6 observations). Suppose we increase the number of observations by adding figures about Spain from Margraf et al. (2020), who use self-reported measures of adherence to containment behaviours. In that case, the correlation coefficient does not change, but statistical significance improves (p-value = 0.0090, with N = 7 observations).

This evidence provides some support in favor of the validity of our measure of compliance, although only in levels. We could not find other measures of compliance over time to test the validity of our measure.

Figure C2: Correlation between two measures of compliance.



Note: the experimental data from Becher and colleagues have been expanded to add Spain to the set of considered countries using data from Margraf and colleagues.

Source: Data are sourced from Oxford Policy Tracker (Hale et al., 2020) and Google Mobility Data (Google, 2020). Non-compliance is issued from the paper by Becher et al. (2020) and Margraf et al. (2020).

Appendix D: Validity of the trust measures

For the same reasons mentioned in Appendix C, it is legitimate to doubt the validity of our measures of trust. Also in this case, measures of trust in others and in institutions are not available for the months considered in the present analysis. Therefore, we compare the average yearly measures of trust with data provided by other sources.

Figure D1 shows the average yearly trust computed using our data (y-axis). Trust is lowest in France followed by Spain, Germany, Italy, United Kingdom, Australia and New Zealand. The Spearman rank correlation test indicates that the ranking based on our trust measure correlates at 71% (significant at 10%) with the rank based on a survey-based measure of trust sourced from the World Values Survey (2018) - European Value Study (2017-2020) integrated data.

Figure D1: Association between trust and trust sourced from survey data.

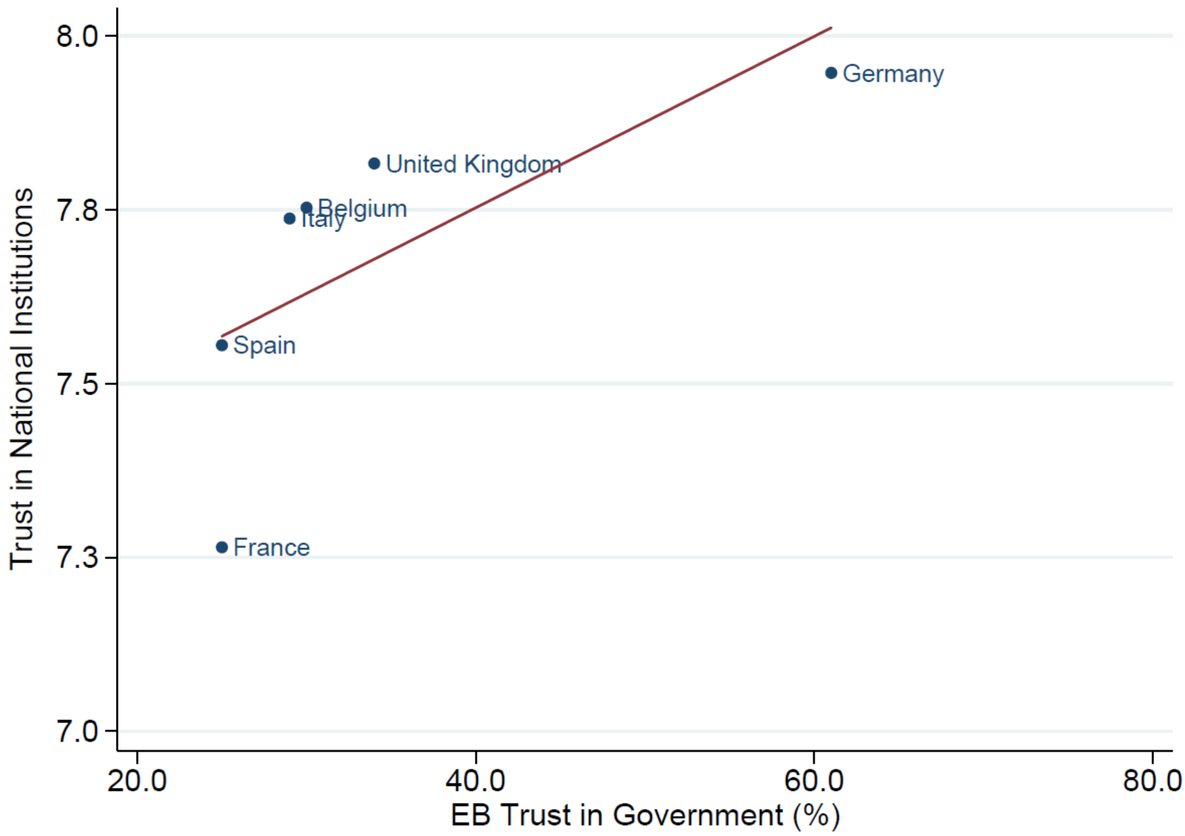
Note: Trust is the average score for each country in 2020. The Spearman correlation coefficient is 0.714 (Prob > |t| = 0.0713, N = 7).

Source: Trust is sourced from the project "Preferences Through Twitter" with the support of FNR, UJ and AUT. Survey measures of trust are sourced from the World Values Survey (2018) - European Value Study (2017-2020) integrated data. Data for Belgium, Luxembourg and South Africa are missing.

Figure D2 shows the correlation between our measure of trust in institutions (y-axis) with a survey-based measure of trust in national government sourced from Eurobarometer. The Spearman rank correlation coefficient is 0.98 (significant at 1%). Importantly, the average trust in institution sourced from Twitter is based on data harvested by country over the period mid-July to the end of August 2020, i.e. the same period when the Eurobarometer was fielded.

This evidence, although not based on correlations over time, provides suggestive evidence in favor of the validity of our measures of trust. We could not find other measures of trust over time to test the validity of our measures.

Figure D2: Trust in national institutions correlates with the share of people trusting the government.



Note: Trust in National Institutions and the share of people trusting the government are the averages by country over the period mid-July to the end of August, i.e. the same time the Eurobarometer was collected. The Spearman correlation coefficient is 0.98 (Prob > |t| = 0.0000, N = 6).

Source: Trust in National Institutions is sourced from the project "Preferences Through Twitter" with the support of FNR, UJ and AUT. The share of people trusting the government is from the Eurobarometer (European Commission, 2020), Summer 2020.

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