Contagious COVID-19 policies: Policy diffusion during times of crisis

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Abstract

The COVID-19 crisis demanded rapid, widespread policy action. In response, nations turned to different forms of social distancing policies to reduce the spread of the virus. These policies were implemented globally, proving as contagious as the virus they are meant to prevent. Yet, variation in their implementation invites questions as to how and why countries adopt social distancing policies, and whether the causal mechanisms driving these policy adoptions are based on internal resources and problem conditions or other external factors such as conditions in other countries. We leverage daily changes in international social distancing policies to understand the impacts of problem characteristics, institutional and economic context, and peer effects on social distancing policy adoption. Using fixed-effects models on an international panel of daily data from 2020, we find that peer effects, particularly mimicry of geographic neighbors, political peers, and language agnates drive policy diffusion and shape countries’ policy choices.

KEYWORDS
COVID-19, emulation, peer effects, policy diffusion, policy mimicry

INTRODUCTION

The SARS COVID (COVID-19) pandemic created a global crisis and led to the rapid uptake of measures designed to contain the spread of the novel coronavirus. Similar social distancing containment policies, such as school and workplace closings, movement restrictions, and limitations...
on public interaction, have been implemented all over the world. It is difficult to ascertain an obvious pattern to the spread of the policy response. Policy diffusion theory establishes that responses result from a combination of internal country characteristics and external pressures from international peers, such as interactions with trading partners and geographic neighbors, political pressure, or idiosyncratic emulation of other countries’ policy responses (Shipan & Volden, 2012). However, current theory does not sufficiently account for the variety of mechanisms directing the interdependent spread of policy (Douglas et al., 2015), overemphasizing geography to the exclusion other diffusion pathways (Nicholson-Crotty & Carley, 2018). More studies employing hybrid models that integrate spatial and mechanism-based diffusion patterns (Mitchell, 2018) and research explaining the characteristics and mechanisms driving policy spread are needed to develop a more complete view of how policy diffusion takes place (Jordan & Huitema, 2014), particularly during periods of crisis where ambiguity, uncertainty, and stakes are high. Previous research has demonstrated that policy diffusion changes over time (Heggelund et al., 2019), but little has been done to investigate policy diffusion in early stages of crisis before policy makers have thoroughly vetted policy alternatives. Furthermore, the diffusion literature often lumps policy learning and emulation together (Karch, 2007), failing to distinguish between these distinct processes. We leverage data from early in the COVID-19 pandemic, spanning 2020, to investigate a period of crisis, isolating international policy emulation and identifying the primary pathways of diffusion across which countries’ policy makers imitate one another.

The COVID-19 pandemic provides a uniquely salient and dynamic context to study diffusion at the international level. Applying policy diffusion theory explains the timing of seemingly arbitrary combinations of policies enacted around the globe and the influence of different diffusion mechanisms by comparing the extent of policy spread across different types of international relationships. We seek to understand the contribution of internal and problem characteristics to a country’s coronavirus response and the extent to which countries’ policy adoptions are also a function of external drivers. This approach helps refine our understanding of policy diffusion theory by providing a comparative look at several pathways of diffusion. Our analysis provides insight into how policy makers react to their peers when making rapid decisions in times of crisis or in situations with high levels of uncertainty.

Policy diffusion theory breaks down policy adoption as a function of internal and external determinants (Berry & Berry, 1990). Internal determinants include problem characteristics in a country, political institutions and context, economic resources, and governance capacity (Canon & Baum, 1981; Huang et al., 2007; Lee & Koski, 2015). External drivers of policy diffusion are less well understood, though recent theoretical advances borrow from research examining diffusion between states and subnational governments suggesting that a combination of coercion, competition, learning, and emulation captures relationships between political bodies that help explain the diffusion of policies (Shipan & Volden, 2008). While neighboring countries, trading partners, and language similarities are typically used as proxies to capture relationships between countries (Berry, 1994; Mintrom, 1997; Mooney, 2001; Stadelmann & Castro, 2014), the mechanisms that lead countries to ultimately adopt a policy at a particular point in time are not fully understood (Jordan & Huitema, 2014).

In the traditional model of policy diffusion, states or countries assess and learn about the outcome of policy choices to adopt successful policies. However, the case of COVID-19 is unique in that, as an international crisis, rapidly changing conditions do not allow for a complete evaluation of policy impact prior to government action. Learning about COVID-19 is dynamic and takes time to develop and disseminate (Osei-Kojo et al., 2022), leading governments to observe actions taken by other countries and react quickly, often with limited information about likely
policy impacts. The unprecedented speed of the pandemic required rapid policy changes without alterations in the underlying institutions that are thought to drive policy change.

The rapidly changing policy landscape was particularly prevalent during the earliest months of the pandemic when the virus was first spreading worldwide, although high levels of uncertainty have persisted. The science on non-pharmaceutical interventions was unsettled through 2020 as new peer-reviewed studies emerged (Haug et al., 2020) and critics continued to question whether strict lockdowns were justified (America’s two largest states are fighting COVID-19 differently, 2021). Policy makers are posed with uncertain dilemmas over how to apply social distancing measures as new strains of COVID-19 emerge (CDC, 2021a), economic conditions change, and the need for measures in conjunction with potential vaccines remains unclear (CDC, 2021b). While the COVID-19 pandemic is a uniquely extreme example of a case where uncertainty hampers decision making, this is hardly exclusive to a pandemic. All policies and situations contain some degree of uncertainty and the need for policy makers to make decisions without complete information (Simon & March, 1958). Uncertainty about characteristics and outcomes are endemic to all policy decisions. The emulation of peer countries is likely a response to this uncertainty. Rather than making decisions independently without good information, countries take cues from one another. This process of cue-taking is not so different from processes that drive decision making by various political entities, as well as emulation processes that describe firm or individual behavior in many other contexts (e.g., Conley & Udry, 2010; Still & Strang, 2009). In this paper, we explore COVID-19 social distancing policy responses by leveraging a unique set of dynamic panel data. To understand policy response, we take the advantage of a daily-variant index of country-level policy responses. We model policy response as a function of a country’s problem conditions (observed cases of COVID-19), problem characteristics in connected countries, and the interaction of the country’s institutional, political, and economic context with problem characteristics. This allows us to compare the impacts of different international relationships on a country’s policy response, analyzing the extent of policy diffusion across four different pathways: geographic proximity, economics, politics, and language.

Our results provide an improved understanding of the pattern of rapid policy change observed during times of crisis and a deeper understanding of the mechanisms guiding policy diffusion processes at the international level. Policy choice ultimately determines the impact of policies, making this research important to understand the impact of policy choice on COVID-19 cases and mortality.

We find that the emulation of peer countries, particularly neighboring countries and countries that have similar political systems or languages, drives policy adoption for COVID-19 social distancing policies. Conversely, we do not find robust effects of problem conditions, as measured by a country’s confirmed cases, impacting social distancing policy adoption. Furthermore, we find limited support for country-level resources, characteristics, or political systems driving the adoption of social distancing policies in response to a changing number of cases. These results suggest that in a rapidly changing problem environment with high uncertainty over the impact of potential policies, countries default to mimicking neighboring and politically or linguistically similar countries. This pattern of adoption explains the shape and scope of the global policy response to COVID-19.

THEORY, CONTEXT, AND HYPOTHESES

The COVID-19 pandemic precipitated rapidly changing social distancing policies across countries. Policy adoption is likely a function of the institutional environment in a country, the extent
of the COVID-19 virus, and external pressures. While the implementation of containment policies should be driven by problem conditions such as the number of COVID-19 cases and deaths detected in a country and country-specific risks and resources, policy response is filtered through its institutional environment, with different governance configurations producing different policy responses. Due to immense media and social pressure, policy responses may be shaped, at least in part, by pressures external to a country’s own political and economic institutions or the characteristics of the problem itself (Shipan & Volden, 2012). Herding or bandwagoning behavior is common (Krause et al., 2016), with governments rapidly emulating policies adopted by other countries.

Policy mimicry, also termed policy emulation, captures peer effects of policies for reasons other than policy learning, competition, or coercion (Shipan & Volden, 2008). This occurs when a country’s policy makers imitate the decisions of their peers without thoroughly evaluating those decisions or understanding how effective they might be (Karch, 2007; Meseguer, 2006; Simmons et al., 2006). The conditions in which emulation is more likely to occur remain unclear, but it seems likely to be a response by decision makers to uncertainty. When faced with a lack of information or significant uncertainty, political entities, firms, and individuals may be more likely to take cues from their peers. Policy makers imitate governments that are perceived as credible (Walker, 1969) or identify states with similar characteristics as worthy role models (Brooks, 2005; Simmons & Elkins, 2004). Governments have been found to imitate those with similar political and ideological leanings (Bromley-Trujillo et al., 2016; Volden, 2006). However, other potential pathways for emulation remain poorly understood. Few studies have investigated when governments rely on emulation or compare which governments they choose to imitate. Due to the rapid spread of the virus, the need for swift policy responses, and quickly shifting conditions creating daily variation, the case of COVID-19 provides a unique opportunity to study the diffusion of policy through emulation.

Below, we detail several hypotheses regarding the adoption of social distancing policies. Domestic problem characteristics are known to guide how governments respond (Mohr, 1969; Walker, 1969). Confirmed COVID-19 cases are an important indicator of pandemic conditions and have been used by national and international health organizations as a relevant measure throughout the COVID-19 crisis (CDC, 2022; WHO, 2022a). We expect that when COVID-19 cases increase, governments will increase social distancing policies to reduce virus spread (Adolph et al., 2020). Social distancing policies are thought to be the primary way that governments can address the spread of the virus, in the absence of pharmaceutical (vaccine or treatment) solutions (Courtemanche et al., 2020).

**H1: Problem Conditions**

*An increase in the number of confirmed cases increases the adoption of social distancing policies.*

Different political and governance systems will produce different responses to identical threats (Adolph et al., 2020). Local government characteristics, institutions, and groups help drive the likelihood of policy diffusion (Godwin & Schroedel, 2000). The nested institutional arrangements present within different governance units shape the incentives and decision-making contexts that policy makers face, moderating their likelihood of emulating peer policies (Eom et al., 2017). Literature on crisis management suggests that leaders in democratic countries with a free press who may face swift and harsh retribution from the media or ballot box may be more likely to take quick and decisive
action (Baekkeskov, 2016; Besley & Burgess, 2002). Especially during pandemics, elected officials tend to defer to experts (Baekkeskov & Rubin, 2014). Countries that constrain executive power, via systems of checks and balances, and are more open, having more transparent and collaborative public agencies (Schnell & Jo, 2019), may be more likely to respond proactively. Democracies may also put a higher priority on the well-being of their citizens (Besley & Kudamatsu, 2006). On the other hand, recent work on authoritarianism has suggested that less-democratic regimes may be able to act more quickly because they do not have to rely on elections for legitimacy (Chen et al., 2016; de Brito et al., 2017; Malesky & Schuler, 2010; Truex, 2016). This is especially true in countries like China where the regime relies on performance legitimacy, or the effectiveness of its governance (Yang & Zhao, 2015; Zhu, 2011). Additionally, democratic regimes provide more venues for pushing back against restrictive policies, as protests against social distancing measures in many democracies have shown, making it easier for authoritarian regimes to maintain unpopular containment policies.

**H2-A: Political Democracy**

The extent of democracy in a country impacts the adoption of social distancing policies.

Fukuyama (2020) argues that competence and effectiveness of the state will determine COVID-19 responses. Some literature suggests that states with higher institutional capacities might take more decisive and dramatic actions (Kahn, 2005; Persson & Povitkina, 2017). On the other hand, a more capable regime might feel comfortable enacting less stringent social distancing measures, confident in its ability to deal with the outbreak through contact tracing, medical care, and testing, as well as its ability to rapidly implement effective social distancing efforts when necessary. This is illustrated by the contrast between the relaxed approach of high-capacity Sweden (Karlson et al., 2020) and the draconian measures taken in lower-capacity India (Krishnan, 2020). While internal political and economic institutions can have varied impacts based on a country’s specific context, they are important factors influencing how policy decision makers behave.

**H2-B: Political Effectiveness**

National governance impacts the adoption of social distancing policies.

Given the anarchic international system and lack of global governance over international health, we do not observe significant international pressure coercing countries to adopt social distancing policies. The World Health Organization (WHO) has issued guidance for countries which could be interpreted as international coercion (WHO, 2022b). The first WHO guidance detailing a comprehensive package of materials on infection prevention, testing, risk communication, and related topics was announced on January 10th, 2020 (WHO, 2022b) but we observe no policy changes in the immediate aftermath of that release. The WHO continued to release information and guidance documents related to latest science and potential best practices for dealing with the pandemic as the most up-to-date understanding of COVID-19 evolved. While there is no way for us to uniquely identify the impact of this coercion on individual countries, the WHO issues blanket guidance to all countries in the world and nearly every country is a member of the organization so these releases should not bias our investigation.

Furthermore, while countries formulate policy responses as a function of internal problem characteristics and political and economic institutional contexts, the limited amount of time...
available to implement policy to address COVID-19 inhibits policy learning. When countries have the opportunity to observe the results of policy experiments conducted by other countries, they are able to build understanding, learn, and rationally adopt successful policies. In this case, countries did not have time to allow this process to take place and are largely reacting to observed policy adoptions by other countries by making rapid decisions to adopt similar policies (or not). Many studies employ metrics of diffusion (Karch, 2007; Weyland, 2005) without clearly specifying diffusion or lumping disparate processes such as learning and emulation together (Karch, 2007; Matisoff, 2008; Matisoff & Edwards, 2014; Mowery, 2011).

Emulation and learning are often confounded in the literature and are difficult to distinguish statistically (Boehmke, 2009). From both theoretical and practice perspectives, however, it is important to distinguish learning from emulation and to distinguish them from other processes driving policy behavior (Gilardi, 2016; Shipan & Volden, 2012). We draw upon definitions of policy learning which involve “second-order” reflection about the costs and benefits of a particular policy, as well as an iterative process that builds on experience associated with policy performance (Grin & Loeber, 2006; Hall, 1993; Heclo, 1974). While there are significantly different conceptions of learning within the policy diffusion literature (Bennett & Howlett, 1992), all draw upon changes in behavior that result from experience (e.g., Etheredge, 1981; Heclo, 1974; Rose, 1991; Sabatier, 1987). In these definitions, learning is purposive, based on experience, and results from improved understanding (Meseguer, 2005). In contrast, policy emulation is a less rational process (Meseguer, 2005) that has been likened to mimicry where countries isomorphically implement similar policies (DiMaggio & Powell, 1983) without considering particular problem contexts or institutional fit. Some recent studies have attempted to tease emulation from learning using carefully defined metrics to capture learning through international organizational membership (Cao, 2010; Go, 2016; Zhou et al., 2019). However, there is still a lot of work to do to untangle emulation from learning. Mechanisms of policy learning have received the lion’s share of attention in the literature, while emulation has received less theoretical and empirical attention.

In the case of COVID-19, policy learning is dynamic and takes time to develop from information acquisition to understanding and implementation (Osei-Kojo et al., 2022). Learning about the success of social distancing policies is limited by both short time horizons and the rapid policy responses necessitated by the virus. Thus, by leveraging various relationships between countries, we can cleanly identify emulation effects, as states have needed to rapidly adopt social distancing policies to address COVID-19 without evidence of the costs, benefits, or impacts required by policy learning. A key question in the emulation literature relates to which countries another country might copy. While many potential mechanisms may drive emulation, policy diffusion studies often remain one-dimensional, excluding alternative mechanisms from the conversation (Adolph et al., 2020; Nicholson-Crotty & Carley, 2018).

Research shows that governments often take cues from their geographic or regional neighbors (Chandler, 2009; Liu & Yi, 2020; Motta, 2018; Rai, 2020) and some authors have suggested that geographic diffusion can capture a number of different causal mechanisms including competition, coercion, learning, and emulation (e.g., Shipan & Volden, 2008; Zhou et al., 2019). Geographic competition has been identified as an important driver of diffusion in numerous policy contexts (Baybeck et al., 2011; Berry & Berry, 1990; Cao & Prakash, 2012; Fay & Wenger, 2016; Woods, 2006). In the case of COVID-19, as with other health policy analyses (e.g., Boehmke, 2009), social distancing policy responses may engender economic competition between neighboring countries since social distancing is believed to be deleterious for economic performance. We
therefore expect countries to learn from their regional neighbors when making decisions about how to respond to COVID-19.

Geographic proximity is not the only factor in play. There is some evidence indicating that as the impacts of different diffusion mechanisms change over time, the importance of geographic contiguity declines relative to other factors (Mallinson, 2021). The information driving diffusion comes through a wide variety of conduits (Mossberger & Hale, 2002) and it is critical to recognize the impact of alternative factors. Numerous mechanisms related to trading partners, political culture, language group, and colonial relationships have been suggested and tested throughout the literature (e.g., Saikawa, 2013; Stadelmann & Castro, 2014; Zhou et al., 2019).

Trading partnerships are a likely conduit of diffusion at the international level for several reasons. An important trade relationship precipitates regular interaction between business and policy leaders. Average people also tend to pay more attention to nations they trade with, even if it is only to note trade deficits or changes in the price or availability of certain goods, as the United States did with China in the early days of its pandemic. Decision makers have been shown to emulate the policies of countries that are politically similar to their own to reduce exposure to political risk (Baldwin et al., 2019). We expect countries to closely emulate their political peers. In addition to politics, policy diffusion can be driven by social influence, as increased communication and coordination between countries invites the exchange of ideas and policy diffusion (Kammerer & Namhata, 2018). Cultural and lingual similarity between countries can increase the likelihood of policy diffusion, particularly if these similarities engender increased communication.

Given substantial literature that suggests a range of potential mechanisms for peer diffusion, we test several metrics of peer emulation (geographic neighbors; trade partners; political peers; cultural peers, as measured by language set) to determine empirically robust diffusion patterns leading to a third set of hypotheses.

H3: Peer Effects

Countries enact policies emulating their (A) geographic neighbors, (B) trade partners, (C) political peers, and (D) language peers by adopting increased stringency of social distancing policies as their peers’ policy stringency increases.

It is possible that rather than responding to policies implemented by their peers, countries are responding to the number of COVID cases in neighboring countries. This might be either because they expect cases to spill across borders (most likely with geographic neighbors or trading partners) or because their governments and citizens are influenced by what is happening in a country seen as similar to themselves (most likely with political or linguistic peers). As a mechanism to understand the extent to which countries are mimicking the policy context of each of their peers, versus attempting to quickly match their own policy context conditioned on the problem characteristics of peer states, we test peer states’ problem characteristics as a driver of policy adoption.

H4: Peer Problem Conditions

Countries respond to problem conditions in peer countries including geographic neighbors, trade partners, political peers, and language peers by adopting increased social distancing policies as COVID-19 cases in peer countries rise.
MATERIALS AND METHODS

We use a variety of sources to construct a panel of daily international COVID-19 data covering the 12-month period from January through December of 2020. First, we gather data on relevant pandemic variables from secondary sources. Our primary data come from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2021). This dataset aggregates daily information on the number of confirmed COVID-19 cases in each country and their government’s policy responses to the pandemic. While regional testing capabilities vary, potentially biasing observations of COVID-19 cases in different countries, alternative available measures have inconsistencies as well. Recent research points out the limitations of mortality as a consistent measure of pandemic impacts due to variance in testing and reporting around the world (Beaney et al., 2020; Clarke et al., 2021). The number of deaths resulting from COVID-19 infection is dependent on healthcare capacity and demographics, both of which vary across countries. Deaths also do not account for the large number of COVID-19 cases which do not require hospitalization. Finally, deaths are a lagging indicator of the spread of COVID. Leaders were unlikely to wait for deaths to accumulate to make policy decisions, especially in the early days of the pandemic. For all these reasons, we use confirmed cases to understand countries’ problem conditions.

We interpolate missing data points for COVID-19 cases since cases can be estimated consistently, replacing missing observations between known values with intermediate values and zeros before a country’s first case. OxCGRT provides data on a variety of policies related to COVID-19 including social distancing. We use these data to create an index of social distancing policy stringency. We measure this index as the sum of a country’s policy stringency across five areas related to social distancing: school closures, workplace closures, public event cancelations, public transport closures, and internal movement restrictions. This measure enables us to understand the intensity of social distancing enforced in each country. Since each type of policy is different and can be implemented at varying degrees, they are coded on different scales (Thomas et al., 2020), resulting in a maximum value of 12 across these five policy areas in our social distancing index. This index captures both the implementation and repeal of social distancing policies over time. It serves as our dependent variable and allows us to investigate international diffusion of social distancing efforts rather than individual policies from among the suite of efforts aimed at limiting the spread of COVID-19. Table 1 provides more detailed information on index composition.

China was the first to mandate social distancing restrictions in all five of these areas. It implemented school closures starting on January 26th and was followed by several nearby countries over the following week. No other school closures were implemented until the end of February when Italy shut down its schools, ushering in widespread adoption of similar policies. China implemented the first workplace closures even earlier on January 16th but was only followed by Mongolia (which closely mirrors China’s policy making in all the areas we study) until rapid rollout occurred around the world over a month later. However, the vast majority of workplace closures outside of China at this point took the form of recommendations or partial closures signifying a reticence to adopt strict restrictions. Event closures were also pioneered by China, starting on January 22nd after which there was a steady stream of adoptions around the world with little apparent temporal or geographical clustering. China then implemented the first transportation closures a day later on January 23rd and was shortly followed by Mongolia before widespread rollout began in mid-March after adoption by Paraguay on March 5th. China implemented the first internal movement restrictions on January 23rd as well, followed by gradual rollout of similar policies in many countries over the next several months.
We control for countries’ political characteristics with the Varieties of Democracy (V-Dem) dataset, commonly used in the political science literature (e.g., Ballard-Rosa et al., 2021; Treisman, 2020). V-Dem compiles a democracy index from countries’ levels of freedom of association, clean elections, freedom of expression, elected officials, and the share of the population with suffrage (Coppedge et al., 2020). States’ administrative capacity is measured by the Worldwide Governance Indicators’ (WGI) 2019 estimate of government effectiveness which considers the quality of public service provision and bureaucracy, the competence and independence of the civil service, and the credibility of the government’s commitment to policies (Kaufmann et al., 2010). We also use international government organization (IGO) membership to measure learning by countries regarding policy impacts in other countries (Zhou et al., 2019). We include additional socio-economic variables to control for economic factors such as Gross Domestic Product (GDP) per capita adjusted for Purchasing Power Parity (PPP) (World Bank, 2020), global travel as the number of international tourists who arrived in that country (Moosa & Khatatbeh, 2021; World Bank, 2020), and critical health factors such as the percentage of the population over 65 years old (Hashim et al., 2020; Zheng et al., 2020), hospital beds per capita, and healthcare spending as a percentage of GDP (Verelst et al., 2020; WHO, 2020). All independent variables are measured per capita and in 2020 international dollars where appropriate.

Second, we supplement the V-Dem democracy index with international connectivity matrices from the Correlates of War Project (COW) and the Centre d’Etudes Prospectives et d’Informations Internationales (CEPII) to measure the interconnection between countries in four areas: geography, economics, politics, and language. These connectivity metrics allow us to investigate

| TABLE 1 Social policy stringency index |
|---------------------------------------|
| **Policy**                              | **Description**               | **Scale**                                      |
| School closures                        | Schools and universities closed| 0: no measures                                 |
|                                       |                               | 1: closures recommended or schools open        |
|                                       |                               | with alterations                               |
|                                       |                               | 2: closures required for some schools (e.g.,  |
|                                       |                               | high schools)                                 |
|                                       |                               | 3: closures required for all schools           |
| Workplace closures                     | Workplaces closed (recommended| 0: no measures                                 |
|                                       | work from home)                | 1: closures recommended or work open           |
|                                       |                               | with alterations                               |
|                                       |                               | 2: closures required for some sectors          |
|                                       |                               | 3: closures required for all non-essential     |
|                                       |                               | workplaces                                     |
| Public event cancelations              | Cancelation of public events   | 0: no measures                                 |
|                                       |                               | 1: cancelations recommended                    |
|                                       |                               | 2: cancelations required                       |
| Public transportation closures         | Public transportation shutdowns,| 0: no measures                                 |
|                                       | reductions in volume, or restrictions| 1: closures recommended or reductions in volume|
|                                       | to access                      | 2: closure required or access restricted        |
| Internal movement restrictions         | Restrictions to domestic travel between cities and/or regions | 0: no measures | 1: travel recommended against | 2: travel restricted |
diffusion across different signaling pathways and examine which countries policy makers emulate and why.

Geographic data come from COW and are coded according to trans-oceanic proximity. Two countries are connected if they border one another or are separated by less than 400 miles of water (COW, 2020). We measure economic proximity via directional trade from COW (Barbieri et al., 2009). Countries are economically connected to every country they trade with, so we weight relevant COVID-19 variables in these economic peers by the level of imports they send to their trading partners. Political proximity is a measure of how similar two countries’ governments are to one another. We calculate countries’ political similarity as the difference between their V-Dem democracy scores and weight political peers by this similarity. Finally, we use language similarity from CEPII (Melitz & Toubal, 2014). The CEPII dataset calculates language similarity based on ethnologue classifications of language trees as in Fearon (2003) and Laitin (2000). We weight relevant variables by linguistic similarity between language peers. We then calculate the mean policy stringency and number of COVID-19 cases for connected countries in each group and lag all time-dependent variables by one day to allow a minimum amount of time for policy implementation. We also interact the time-invariant control variables in our model with each countries’ confirmed COVID-19 cases to understand the impact they have in conjunction with the pandemic threat.1 By interacting country-level characteristics with COVID-19 cases, we are able to examine how these variables impact countries’ policy responses conditional on pandemic conditions and use them in a fixed-effects panel model. We merge all these data together into an unbalanced panel dataset at the country-day level.2 Descriptive statistics are in Table 2.

Fixed-effects methods are effective at controlling for unobserved heterogeneity between groups (Allison, 2009) and drawing causal inferences from panel data (Gangl, 2010). We use a series of linear fixed-effects models with robust standard errors to test our hypotheses. Linear fixed-effects models reliably fit our data and provide the most parsimonious and interpretable form for our analysis. This methodology can provide accurate estimates since it controls for country-level individual-specific effects that are correlated with variables in our model (Wooldridge, 2010). This is critical due to the numerous unobserved country-level characteristics that can influence both pandemic response and policy choice. This allows us to investigate the impact of neighboring countries’ policy stringency and COVID-19 cases on countries’ policy responses, controlling for a wide set of political, health, and socio-economic factors.

We run a set of models exploring policy diffusion across our four types of international connectivity: geography, economics, politics, and language. In Models 1 through 4, we examine the impact of peer effects for each type of international connection independently, estimating the impact of relevant factors on policy emulation. Then, in Model 5, we test all four connection types against each other as rival pathways of policy diffusion. We also conduct several robustness checks, using alternative specifications of our main model, to test our findings and reinforce the validity of our conclusions. First, we test our model, using an alternative dependent variable measuring overall COVID-19 policy stringency developed by Hale et al. (2020). Next, we test country-level internal determinants independently. Finally, we add an exogenous time trend to the model to test whether ongoing international changes over time alter our results. These robustness checks largely support our primary results, reinforcing our findings. Additional details and the results for each of these robustness checks are included in the Appendix A.
| Variable                        | Description                                                                 | n    | Mean      | Std. dev. | Min/max |
|--------------------------------|-----------------------------------------------------------------------------|------|-----------|-----------|---------|
| Policy stringency              | Social distancing policy stringency index                                   | 51,227 | 5.97      | 4.03      | 0/12    |
| COVID-19 cases                 | Confirmed COVID-19 cases per capita                                         | 51,240 | 4.17e−03  | 9.12e−03  | 0/0.10  |
| Democracy index                | Level of democracy (Scale of 0 to 1)                                         | 47,053 | 1.36e−03  | 4.29e−03  | 0/0.06  |
| Government effectiveness       | Level of government effectiveness (Scale of −2.5 to 2.5)                    | 49,410 | 1.99e−03  | 9.16e−03  | −0.03/0.14 |
| IGO membership                 | Number of intergovernmental organizations engaged in by country              | 50,874 | 0.30      | 0.67      | 0/6.49  |
| % over 65                      | % of total population over 65 years old                                     | 49,776 | 0.04      | 0.12      | 0/1.31  |
| Hospital beds                  | Hospital beds (per 1000 people)                                             | 50,142 | 0.01      | 0.04      | 0/0.44  |
| Health spending                | Current health expenditure per capita (PPP 2020 international $)             | 50,142 | 11.90     | 38.50     | 0/605.17 |
| Arrivals                       | International tourism, number of arrivals (millions)                        | 49,776 | 5.47e04   | 2.39e05   | 0/4.89e06 |
| GDP                            | Natural Log of GDP per capita (PPP 2020 international $)                     | 49,410 | 0.04      | 0.09      | 0/0.89  |
| Geography                      | Weighted per capita                                                         |       |           |           |         |
| Neighbor stringency            | Mean social distancing policy index of neighboring countries                | 47,214 | 6.21      | 3.73      | 0/12    |
| Neighbor cases                 | Mean number of confirmed COVID-19 cases in neighboring countries            | 47,214 | 4.37e−03  | 8.15e−03  | 0/0.07  |
| Trade                          | Weighted by imports (millions $)                                            |       |           |           |         |
| Trade partner stringency       | Mean social distancing policy index of economic peers                       | 49,776 | 2.08e−04  | 2.11e05   | 0/3.52e06 |

(Continues)
| Variable                  | Description                                               | n   | Mean      | Std. dev. | Min/max     |
|--------------------------|-----------------------------------------------------------|-----|-----------|-----------|-------------|
| Trade partner cases      | Mean number of confirmed COVID-19 cases in economic peers (millions) | 49,776 | 2.06e07   | 1.76e08   | 0 4.39e09   |
| Politics                 | Weighted by political similarity                          |     |           |           |             |
| Political peer stringency| Mean social distancing policy index of political peers     | 47,053 | 2.70e07   | 1.84e08   | 0 3.88e09   |
| Political peer cases     | Mean number of confirmed COVID-19 cases in political peers | 47,053 | 1.99e11   | 1.75e12   | 0 1.11e14   |
| Language                 | Weighted by lingual similarity                           |     |           |           |             |
| Language peer stringency| Mean social distancing policy index of language peers     | 32,208 | 4.61      | 4.87      | 0 41.33     |
| Language peer cases      | Mean number of confirmed COVID-19 cases in language peers | 32,208 | 1.63e05   | 3.57e05   | 0 6.18e06   |

**Table 2** (Continued)
CONTAGIOUS COVID-19 POLICIES

RESULTS

The results, displayed in Table 3 and Figure 1, demonstrate the impact of peer effects and internal characteristics on countries’ level of social distancing policies. The relationships between country-level characteristics and policy stringency, conditional upon the number of COVID-19 cases, illustrate how different countries respond to changing problem conditions. These results provide surprising findings for H1 and H2. Our main model (Model 5) suggests that the number of confirmed cases per capita has a negative influence on policy stringency, contingent on a country’s health spending and the percentage of its population that are over 65 years old. Since hospital capacity, as other resources related to health spending, is a substitute for social distancing (Adolph et al., 2020), we observe countries with higher levels of health spending increase the stringency of their social distancing policies less in response to rising cases. However, contrary to expectations, we also see countries with more aged populations doing the same. Individuals over 65 years old have a higher risk of serious complication from COVID-19 (CDC, 2021c; Hashim et al., 2020), so we should expect countries with a higher percentage of people in this vulnerable category to strengthen their social distancing policies more as cases rise to protect aging members of their population. Our results indicate the opposite. These results are weakly significant and are not robust across our other four models, examining peer effects individually. Other internal characteristics show mostly insignificant results across our models. The only exception is IGO membership, often used to capture countries’ learning about policy impacts (see Zhou et al., 2019), which is significant only in the linguistic peer model (Model 4). This model indicates that countries that are hit harder by the pandemic respond more to IGO involvement, but this result disappears after we control for all four types of peer influence. These results are intriguing because they demonstrate the overall insignificance of internal characteristics or problem conditions in determining policy choices, emphasizing the dominant importance of mimicry among policy decision makers.

Models 1 through 4 reveal support for all four peer effect hypotheses (H3) when the peer effect mechanisms are tested individually, demonstrating that a country’s policy choices are influenced by its peers’ policies. Countries are more likely to implement a policy change the very next day after a peer country changes its social distancing policies. Model 5, which tests all four peer relationships against each other, reveals strong support for geographic, political, and language peer relationships as statistically significant predictors of social distancing policy adoption. Countries are more likely to adopt stricter social distancing policies if their geographic, political, and language peers’ have more stringent policies. For instance, a country’s social distancing stringency index is 0.76 higher for each level increase in the social distancing stringency index of their neighbors. This model provides some limited evidence that countries imitate the social distancing policies of their economic peers as well, but this relationship is weakly significant. Additionally, this model shows that the density of COVID-19 cases in peer countries is only positive and strongly significant in the trade partner model. This may indicate that countries pay more attention to the number of cases in a country with which they are likely to exchange more business travelers. A lack of significance along other diffusion pathways, however, seems to suggest the relative unimportance of pandemic conditions in connected countries for policy decision making. International problem context, measured by the known prevalence of COVID-19 in peer countries, does not drive countries to adopt more stringent social distancing policies outside of an economic context. Figure 1 depicts the results from our primary models with confidence intervals for each variable. These results highlight the importance of geographic relationships,
### TABLE 3  Impact of peer group on social distancing policy adoption

| Variables                  | Model 1  | Model 2  | Model 3  | Model 4  | Model 5  |
|---------------------------|----------|----------|----------|----------|----------|
|                           | Geography| Economics| Politics | Language | All Peers|
| **R-squared**             | 0.685    | 0.042    | 0.042    | 0.476    | 0.716    |
| **Countries**             | 118      | 126      | 127      | 82       | 77       |
| **Observations**          | 40,765   | 43,670   | 44,035   | 28,325   | 26,515   |
| **Policy stringency**     |          |          |          |          |          |
| COVID-19 cases            | −79.15   | 336.60   | 456.60   | −177.40  | −735.30  |
|                           | (324.80) | (284.60) | (285.40) | (492.90) | (536.00) |
| Democracy index           | 11.84    | 6.47     | 2.40     | −34.10   | −5.46    |
|                           | (28.00)  | (36.57)  | (37.18)  | (34.36)  | (25.89)  |
| Govt effectiveness        | 4.49     | 40.52    | 45.41    | 35.21    | −6.64    |
|                           | (29.63)  | (33.24)  | (31.28)  | (46.09)  | (36.62)  |
| IGO membership            | 0.51     | 1.15     | 1.18     | 1.70*    | 0.64     |
|                           | (0.78)   | (0.92)   | (0.95)   | (1.00)   | (0.83)   |
| % Over 65                 | 1.14     | −2.41    | −1.80    | −6.709   | −4.55*   |
|                           | (2.58)   | (3.76)   | (3.94)   | (4.16)   | (2.52)   |
| Hospital beds             | −2.47    | −2.57    | −3.62    | 5.12     | 3.27     |
|                           | (6.74)   | (7.62)   | (7.81)   | (6.72)   | (6.12)   |
| Health spending           | −7.95e−03| −4.05e−03| −2.07e−03| −9.55e−03| −0.01*   |
|                           | (6.73e−03)| (7.57e−03)| (8.04e−03)| (8.82e−03)| (7.08e−03)|
| Arrivals                  | 1.57e−07 | 8.42e−08 | −7.41e−08| −2.47e−07| −1.09e−08|
|                           | (4.26e−07)| (6.25e−07)| (6.66e−07)| (6.14e−07)| (4.89e−07)|
| GDP                       | 9.11     | −30.49   | −43.24   | 21.47    | 81.45    |
|                           | (28.42)  | (25.31)  | (27.70)  | (51.53)  | (53.51)  |
| Neighbor stringency       | 0.87***  |          |          |          | 0.76***  |
|                           | (0.02)   |          |          |          | (0.06)   |
| Neighbor cases            | −32.13*  |          |          |          | −18.94   |
|                           | (16.68)  |          |          |          | (17.26)  |
| Economic peer stringency  | 3.16e−06***|          |          |          | 1.80e−07*|
|                           | (4.60e−07)|          |          |          | (9.69e−08)|
| Economic peer cases       | 2.80e−11 |          |          |          | 1.25e−09***|
|                           | (3.17e−10)|          |          |          | (2.84e−10)|
| Political peer stringency | 2.52e−09***|          |          |          | 1.16e−09***|
|                           | (4.63e−10)|          |          |          | (1.55e−10)|
| Political peer cases      | −1.02e−14|          |          |          | 5.30e−14*|
|                           | (4.03e−14)|          |          |          | (3.17e−14)|
| Language peer stringency  | 0.82***  |          |          |          | 0.19**   |
|                           | (0.17)   |          |          |          | (0.08)   |
political similarity, and linguistic connections in policy adoption and change. The results of our robustness checks are consistent with these findings (see Appendix A).

Interestingly, peer effects appear to be more meaningful in driving the policy environment of a country than the actual number of confirmed cases indicating that internal pandemic conditions are not a major driver of policy choice. The number of confirmed COVID-19 cases per capita does not have a significant direct effect in any of our models. There is some evidence that it indirectly influences policy stringency by moderating several country-level variables, but these results are only weakly significant and somewhat counterintuitive. Overall, our results emphasize the role of mimicry and emulation, particularly of geographic, political, and language peers, driving social distancing policy adoption. In contrast, the relationship of problem context and internal characteristics of with policy response is unclear. Furthermore, the number of confirmed COVID-19 cases present in peer nations does not lead countries to adopt more stringent social distancing policies in most cases, opposing our prediction (H4) and suggesting that international problem context does not play a major role in countries' policy choices. In these models, countries

| Variables           | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---------------------|---------|---------|---------|---------|---------|
| Language peer cases | −1.10e−06** | −6.40e−07** | −6.10e−07** | (5.02e−07) | (2.87e−07) |
| Constant            | 0.73***  | 5.59***  | 5.60***  | 2.25***  | 0.51**  |

***p < .01; **p < .05; *p < .1.

FIGURE 1 Significance of variables for social distancing policy adoption across models 1–5
appear to be significantly less likely to adopt more stringent social distancing policies as the number of cases rises among their geographic and language peers, but these counterintuitive results are weakly significant and do not indicate a straightforward response to pandemic conditions in these countries. The exception to this rule appears to be among international trading partners. Countries do appear to adopt more social distancing policies when COVID-19 case loads rise in their economic peers. This may be the result of high level of expected interaction between people from these countries. International arrivals have been shown to have a major impact on the severity of COVID-19 conditions (Moosa & Khatatbeh, 2021), so policy makers may enact social distancing policies in anticipation of the international interactions that will inevitably take place through trade. However, further research focused on this specific phenomenon is necessary to answer this question. Overall, countries appear to mimic peer countries’ policy choices, regardless of whether or not those peers have high prevalence of COVID-19.

**DISCUSSION AND CONCLUSION**

Our findings contribute to the policy diffusion literature in several ways. First, we isolate the effect of emulation on international policy responses and identify the pathways through which it causes policies to spread. Policy adoption and diffusion are typically considered a function of a country’s problem conditions, political context, resources, and the influence it faces from external peers through mechanisms such as coercion, competition, learning, and emulation (Shipan & Volden, 2012). Learning and emulation are notoriously difficult to distinguish (Boehmke, 2009) and are often confounded. While it is critical to distinguish these processes from one another (Gilardi, 2016; Shipan & Volden, 2012), many authors are unable to do so and investigate their combined effect (e.g., Karch, 2007) limiting understanding of how pure emulation drives policy diffusion. In the case of COVID-19, it is unlikely that coercion, competition, or learning can explain the rapid changes in social distancing policy enacted by different countries. Studying data from a window of time early in the pandemic before learning was possible allows us to adopt a modeling approach designed to isolate peer emulation as a mechanism to explain policy adoption, providing a clear view of how emulation impacts the policy diffusion.

We conduct a multidimensional investigation of international diffusion. Much of the diffusion literature fails to account for the variety of mechanisms driving policy spread (Douglas et al., 2015), focusing on geographic proximity to the exclusion of other potential pathways for diffusion (Nicholson-Crotty & Carley, 2018). By integrating four types of international connection into our model, we identify alternate pathways of diffusion and examine their comparative importance to the spread of social distancing policies in response to COVID-19. The comparison of four different types of international connection allows us to identify the processes by which emulation occurs. Measuring the daily changes in social distancing policies allows for an unusually fine-grained set of rapidly occurring incremental policy changes to identify peer effects. In a situation with high scientific uncertainty and imperfect information, our findings indicate that while geographic proximity is an important driver, it is not the only factor influencing diffusion. Investigation of other pathways, such as political similarity, is also crucial to understanding policy diffusion. Future work that investigates this cue taking by political decision makers and the importance of political peers and geographic neighbors would be a valuable contribution.

In addition to the use of daily variant policy data, our approach offers several additional methodological contributions to the policy diffusion literature. Our fixed-effects methodology controls for country-specific institutional, political, and economic characteristics that do not change in
the short term. By interacting country-level characteristics with daily case counts, we allow these variables to impact policy response conditional on policy conditions, but do not find strong impacts of country problem conditions, political context, resources, or risk factors. This method offers many advantages for policy diffusion research. By controlling for subject-specific effects among the governance units under scrutiny, it provides more statistical power than many of the survival models or event history analyses that are typically applied to policy diffusion questions. This can provide us with more confidence in the causal inferences drawn from the data. When data structure and availability allow, future policy diffusion studies should utilize this methodology.

Finally, our investigation reveals important implications about how policy diffusion guides policy responses during times of crisis. While previous studies have shown that policy diffuses differently at different periods of time in a policy arena (Heggelund et al., 2019), little work investigates its specific processes in the early stages of significant global events. Consistent with concurrent research (Sebhatu et al., 2020), our findings emphasize the role of emulation whereby countries quickly adopt policies mimicking peer states, rather than making decisions based on a more systematic assessment of the problem, context, and potential solutions. We expect emulation to occur early on during a crisis when very little is known about the problem at hand, but we find that reliance on policy emulation remained a strong driver of policy adoption throughout 2020. This could be because one year has simply not been enough time for governments to adequately learn how different policies will work in response to the pandemic. Persistent changes in how we understand the virus, as well as evolution of the virus itself (CDC, 2021a) cast doubt on whether policy makers have yet had sufficient time. However, our results show that international policy makers continued to imitate their peers’ policies throughout 2020, rather than responding to internal characteristics or pandemic conditions, showing the importance of emulation even if learning did occur.

While the COVID-19 pandemic may be an extreme case of changing problem conditions, scientific uncertainty, and imperfect information, policy makers are often forced to make decisions without perfect information. Traditional conceptions of policy diffusion understand governments as policy laboratories that act as testing grounds for novel policies, providing peer governments with the opportunity to observe and rationally adopt policy experiments that turn out to be successful (Elazar, 1972; Volden, 2006). However, in the face of a fast-paced crisis, this model appears to break down. When faced with the spread of COVID-19, countries have not had the time to carefully assess the impact of different policy alternatives and have shifted to simple mimicry. This finding helps explain the seemingly idiosyncratic way in which countries have adopted social distancing policies and demonstrates that states look to their geographic and political peers for cues to guide policy response in a crisis. While the COVID-19 is an extreme case, it seems likely that all governments rely on emulation to assist with decision making in conditions when information is imperfect. When faced with uncertainty about the political, economic, or scientific effects of a potential policy, relying on peers as a decision heuristic reduces the burden on political decision makers to make contentious decisions. It may also provide political cover if decisions result in poor outcomes. The reliance on cue-taking from political peers demonstrates the inherently political calculus driving decision makers when producing policy responses to a problem. While assessing the impact of these policies is beyond the scope of this paper, it is apparent that policy choice has produced meaningful differences in death rates and the spread of the virus (An et al., 2021). The reliance of political decision makers to take cues from political peers has important implications for the severity of the pandemic and its impacts on human mortality around the world. Future research investigating cue-taking among policy makers would be
valuable across a wide range of topics. We expect our findings to apply any situation characterized by rapid change and political, environmental, or scientific uncertainty, indicating that this approach could be a useful framework for understanding policy making surrounding other crises such as economic recessions, military conflicts, or natural disasters.

It is necessary to acknowledge some of the methodological limitations and weaknesses of our study. The differences in the amount of data available for each country impact the number of countries included in our statistical models and may, to the extent to which data availability is correlated with unobserved country characteristics, create varying levels of error rates among our diffusion variables. While this limitation should not undermine our findings and our results are robust, we retain caution when interpreting the strength of our results. Additionally, our data do not capture the impact of experience with past pandemics. While the subject-specific effects in our model help control for countries’ previous experience with health crises, we are unable to estimate the specific impact of historical learning on policy choice. Future research may investigate the role of historical learning in more depth. Furthermore, using national-level data has several implications. First, different countries’ policy-making processes are not uniform. Small centralized countries will often have a consistent COVID policy, while large federal countries may have vastly different policies and problem characteristics. Second, the number of COVID-19 cases and deaths may be reported inconsistently across different countries, so our finding that social distancing policies are not responsive to pandemic conditions may be biased by countries that underreport these statistics to justify inaction. Future research can investigate the accuracy of state statistics and the political machinations employed to justify less stringent pandemic response.

Finally, the index of social distancing policies we use as our dependent variable provides a holistic look at how countries are implementing social distancing in response to COVID-19, but it does not capture diffusion of specific policy choices between states. While our findings are reasonably robust to narrower indexes focused on more specific policies (as established in additional tests not reported here), it is important to emphasize that our results indicate diffusion of the intensity of social distancing across the suite of policies aimed at that goal, applying our results to specific policies from within the overall group would be inappropriate. Furthermore, this dependent variable is a blunt instrument for measuring policy choice and impact. However, it allows us to examine the international spread of social distancing policy more holistically, highlighting how policy contagion has been independent from the epidemic itself, and how countries’ policy choices have not been responsive to best practices, risks, or resources, but are primarily determined by emulating what other peer states have done.

Anecdotal evidence highlights some of the problems associated with this approach. Several Asian countries were able to contain the virus using rapidly implemented social distancing followed by testing, tracing, and wearing masks. This allowed many of these countries to reduce the spread of the virus and move quickly towards reducing social distancing restrictions. Yet, mask wearing in response to both pollution and illness was much more common in East Asia pre-pandemic. This effect should be captured both by our fixed-effects model and by our cultural (language) diffusion variable. While we considered that there might be impacts related to previous experience with pandemics, we could not identify a clear method of controlling for the impact or durability of previous pandemics, especially considering the clear novelty of the challenges posed by COVID-19.

In contrast to East Asia, many Western countries were hesitant to implement social distancing restrictions while avoiding measures like wearing masks, that months later were realized to be effective at inhibiting the spread of the virus. Practices that were later deemed to be relatively low cost and highly effective at reducing the spread of the virus, such as
screening, masks, and contact tracing were slow to be implemented in some countries, while other high-cost policies that have uncertain impacts, like closing schools, were rapidly implemented. From a policy perspective, these patterns of normative emulation have shaped the global policy response to COVID-19, and as a consequence, the health and economic impacts of COVID-19.

The spread of COVID-19 provides a unique context to study international policy diffusion. By investigating countries’ policy responses using policy diffusion theory, we help to explain the timing of related policy implementations around the globe, as well as the influence of different mechanisms of diffusion, by comparing the impact of diffusion across different types of international connections. We find support for a variety of different metrics of measuring peer emulation even in the context of a fixed-effect model that controls for confounding country-specific factors that are often not resolved when using an event history analysis model. Geographic neighbors, trading peers, political peers, and linguistic peers, all exert powerful influence over countries’ social distancing policy adoptions, though geographic neighbors and political peers appear to be the strongest drivers of policy change. These findings deepen our understanding of policy diffusion theory by isolating the impact of policy emulation in the diffusion process, providing a comparison of alternative diffusion pathways alongside geographic proximity, and providing insight into how policy makers react to their peers during times of crisis.

**CONFLICTS OF INTEREST**
The authors have no relevant financial or non-financial interests to disclose.

**DATA AVAILABILITY STATEMENT**
The data included in this analysis are all available from the publicly available datasets from which they were drawn (as described in the manuscript). The final dataset and code used in this study is not publicly available since all of its contents are available elsewhere, but it is available from the corresponding author on reasonable request.

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**ENDNOTES**
1 Time-invariant controls in our model consist of the following: level of democracy, government effectiveness, international governmental organization membership, percent of the population over 65 years old, number of hospital beds per thousand people, health spending per capita, international arrivals per capita, and GDP per capita.

2 The panel dataset is unbalanced due to missing values across different variables in the dataset; see Table 2. Countries which lack robust data are somewhat underrepresented in our data; this could affect results as countries with high levels of data collection may be more likely to participate in international interactions. We lose the most countries due to data availability when examining diffusion through language peers. While there is no indication that these omissions are systematic and our results are findings are not changed by excluding language data, future research employing a richer set of language data would be useful to investigate language-based diffusion in more depth.
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**How to cite this article:** Mistur, E. M., Givens, J. W., & Matisoff, D. C. (2022). Contagious COVID-19 policies: Policy diffusion during times of crisis. *Review of Policy Research*, 00, 1–27. https://doi.org/10.1111/ropr.12487
APPENDIX A

OxCGRT provides information on all COVID-19 policies, not just the social distancing policies we focus on. Hale et al. (2020) construct an index of overall COVID-19 policy stringency covering a diverse set of policy areas. We run Model 5 again using this overall policy stringency index as an alternative specification of our dependent variable. This total policy index comes directly from the OxCGRT dataset and includes 17 different indicators of countries’ responses including policies related to containment (such as social distancing efforts), economics, and public health. The results in Table A1 are largely consistent with our main findings with a few minor exceptions. Domestic COVID-19 cases and GDP per capita appear significant in this model, while percent over 65 years old and health spending do not. However, the impact of domestic cases is contrary to expectations and remains only weakly significant. The only major difference between this robustness check and our primary model is that the number of COVID-19 cases in political peer countries is insignificant, whereas it appears to influence policy adoption in the social distancing index we study in our primary model. These results largely reinforce our primary findings.

| Variables                  | Model 5 (alternate dependent variable) |
|----------------------------|----------------------------------------|
| **R-squared**              | 0.775                                  |
| **Countries**              | 77                                     |
| **Observations**           | 26,516                                 |
| **Total policy index**     | **Coefficient**                       |
| COVID-19 cases             | −5211.00*                              |
| Democracy index            | −98.73                                 |
| Govt effectiveness         | −133.50                                |
| IGO                        | 2.52                                   |
| % Over 65                  | −22.30                                 |
| Hospital beds              | 22.59                                  |
| Health spending            | −0.06                                  |
| Arrivals                   | −6.24e−07                              |
| GDP                        | 561.60**                               |
| Neighbor stringency        | 0.82***                                |
| Neighbor cases             | 26.90                                  |
| Economic peer stringency   | 4.11e−07***                            |
| Economic cases             | 8.18e−09***                            |
| Political peer stringency  | 8.99e−10***                            |
| Politics cases             | 3.29e−13                               |
| Language peer stringency   | 0.14†                                  |
| Language cases             | −4.30e−06***                           |
| Constant                   | 3.80**                                 |

***p < .01; **p < .05; *p < .1.
We also run an alternative specification of our main model, dropping the peer relationship variables, and including only controls. Table A2 provides a look at how these internal country characteristics influence COVID-19 responses without accounting for external, international pressures. In this model, only domestic COVID-19 cases, and GDP per capita can be shown to drive the stringency of social distancing policies and these relationships are only weakly significant, indicating the inefficiency with which we can model policy adoption during times of crisis using only internal characteristics.

Finally, we add an exogenous, daily time trend to our model to check whether our results are driven by international changes in how countries responded to the pandemic over time as seen in Table A3. This controls for potentially important changes in how the international community perceived and reacted to COVID-19, potentially stemming from development in recommendations from international health organizations. There are several minor differences in this robustness check as well. The exogenous time trend we added and GDP per capita are weakly significant in addition to the internal characteristics that display significant relationships in our primary model. Additionally, the number of COVID-19 cases in geographic neighbors appears weakly significant while the effect of COVID-19 cases in political neighbors drop out. However, the results remain predominantly the same and, apart from these minor details, are statistically similar to our primary results.

### Table A2  Impact of control variables on social distancing policy adoption

| Variables               | Model 5 (control variables only) |
|-------------------------|----------------------------------|
|                         | **R-squared** | 0.034 |
|                         | **Countries** | 127   |
|                         | **Observations** | 44,035 |
| **Policy stringency**  | **Coefficient** | (Robust standard error) |
| COVID-19 cases          | 431.73* | (251.54) |
| V-Dem                   | 1.53    | (35.95) |
| Govt effectiveness      | 47.03   | (30.66) |
| IGO                     | 0.99    | (0.91)  |
| % Over 65               | −2.50   | (3.81)  |
| Hospital beds           | −2.71   | (7.67)  |
| Health spending         | −3.89e−03 | (7.59e−03) |
| Arrivals                | 8.71e−08 | 6.20e−07 |
| GDP                     | −38.40* | 22.95   |
| Constant                | 5.65*** | (0.05)  |

***p < .01; **p < .05; *p < .1.
### Robustness check with exogenous time trend

| Variables                      | Model 5 (daily time trend) |
|-------------------------------|----------------------------|
| **R-squared**                 | 0.719                      |
| **Countries**                 | 77                         |
| **Observations**              | 26,515                     |
| **Total policy index**        | **Coefficient**            | **Robust standard error** |
| COVID-19 cases                | −794.60                    | (511.30)                  |
| V-Dem                         | −2.93                      | (26.28)                   |
| Govt effectiveness            | 0.65                       | (36.48)                   |
| IGO                           | 0.44                       | (0.85)                    |
| % Over 65                     | −4.12*                     | (2.42)                    |
| Hospital beds                 | 2.53                       | (6.06)                    |
| Health spending               | −0.01**                    | (7.01e−03)                |
| Arrivals                      | 1.15e−07                   | (4.65e−07)                |
| GDP                           | 87.71*                     | (50.87)                   |
| Daily time trend              | 3.19e−03*                  | (1.67e−03)                |
| Neighbor stringency           | 0.74***                    | (0.06)                    |
| Neighbor cases                | −35.73*                    | (18.64)                   |
| Economic per stringency       | 1.89e−07**                 | (8.94e−08)                |
| Economic cases                | 1.07e−09***                | (3.04e−10)                |
| Political peer stringency     | 1.17e−09***                | (1.32e−10)                |
| Politics cases                | 3.04e−14                   | (2.46e−14)                |
| Language peer stringency      | 0.18**                     | (0.08)                    |
| Language cases                | −9.68e−07***               | (2.65e−07)                |
| Constant                      | 0.27                       | (0.27)                    |

***p < .01; **p < .05; *p < .1.