



Pandemics, Mitigation Measures, and Environment

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Abstract

The paper studies the effects of mitigation measures on environment during a pandemic. Various mitigation measures such as business closures have been imposed to reduce health risks. Such measures also limit economic activities and reduce emissions. Measures disproportionately affect the contact-intensive sectors such as the leisure and hospitality industry, as their economic activities involve more person-to-person interactions. Thus, the extent of emission reduction depends on the severity of a measure and the size of the contact-intensive sectors. Using data on business and restaurant closures, school closures and bans on gatherings across 50 U.S. states during the Covid-19 pandemic, an empirical analysis shows that emissions decrease more in states with a more stringent measure and a larger share of the contact-intensive sectors.

Keywords Pandemics · Mitigation measures · Contact-intensive sectors · Emissions

JEL Classification Q5 · H1 · D6

1 Introduction

During the recent Covid-19 pandemic, nations or states/provinces have implemented mitigation measures to reduce health risks. Such measures have significantly reduced pollutions and emissions,¹ as demonstrated by a large body of research. For example, based on cross-country data, Le Quéré et al. (2020) have estimated that CO₂ emissions have decreased by 27% during the recent pandemic. Muhammad et al. (2020) have also estimated that pollution has reduced up to 30% in some cities such as Wuhan and some countries such as Spain and Italy. Another large literature has studied economics of pandemics, focusing on the trade-off between economic losses and health benefits involved in measures (for example,

¹ A mitigation measure is called a measure for simplicity.

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Alvarez et al. 2020; Eichenbaum et al. 2020; Jones et al. 2020). This paper attempts to contribute to understanding pandemics and environment by combining the two strands of literature.

The first literature considers the effects of measures on environment, namely pollutions or emissions, but ignores economic factors. The second literature, by contrast, concerns the economic losses associated with measures that reduce health risks, but ignores environment. This paper considers economic losses, like the second literature, and environmental benefits, like the first literature. In particular, the paper studies the effects of the stringency of mitigation measures and the size of the contact-intensive sectors on emission reduction.

In the model, the economy consists of multiple sectors that differ in the degree of person-to-person contacts required in production. A measure, intended to reduce health risks, limits economic activities, but affects disproportionately the contact-intensive sectors such as the leisure and hospitality industry. In fact, the news media have typically mentioned that restaurants and hotels have been hit hardest during the recent pandemic (Pietsch 2020; Suneson 2020). The reason is that production in these businesses requires person-to-person interactions and cannot be done online or from home (Koren and Petö 2020; Mongey et al. 2020). The model thus assumes that an increase in the severity of a measure affects mainly the contact-intensive sectors. To the extent that emissions increase with economic activities, the degree of emission reduction resulting from mitigation measures depends on two factors. First, the size of the contact-intensive sectors determines the scope of economic activities that are affected by a measure. Second, the stringency of a measure determines the intensity of restrictions on economic activities. Emissions thus fall more as the size of the contact-intensive sector increases or the stringency of a measure increases.

Using a set of state-level data during the Covid-19 pandemic in the U.S., model predictions are tested. The stringency of measures is based on four indexes regarding nonessential business closures, bans on gatherings, school closures and restaurant closures. For instance, some nonessential businesses are allowed to open with reduced capacity in some states while all nonessential businesses are closed in others. The size of the contact-intensive sectors is represented by the percentage of employment in three industries, leisure and hospitality, trade and transportation, and education and health services. Using the extent of emission reduction in Le Quéré et al. (2020) as the dependent variable, regression results show that states with a more stringent measure or a larger size of the contact-intensive sectors experience a larger percentage reduction in emissions, lending support to model predictions.

This paper is related to a large body of research on the Covid-19 pandemic.² First, a literature has estimated the effects of the pandemic on the level of pollutions (Almond et al. 2020; Le Quéré et al. 2020; Muhammad et al. 2020; Venter et al. 2020). As noted earlier, this literature does not consider economic factors or an economic channel through which measures affect emissions. Han et al. (2020) use GDP to estimate emission reduction in China. Like this paper, they represent a rare example of the analysis of the economic and environmental aspects. However, they do not consider the stringency of a measure or the size of the contact-intensive sectors. Second, another strand of literature has considered the economic effects of mitigation measures in the disease framework. Much of economic research on the Covid-19 pandemic belongs to this literature. The main focus is on the

² A number of strands of literature have studied various aspects of the Covid-19 pandemic, such as the effects of the pandemic on stock prices or on income inequality. These research topics are not directly related to this paper and will not be discussed.

infection externalities that individuals impose on others (Acemoglu et al. 2020; Alvarez et al. 2020; Atkeson 2020; Bethune and Korinek 2020; Jones et al. 2020; Eichenbaum et al. 2020). This literature studies the health-benefit and economic-loss trade-off, involved in measures, but does not consider environmental benefits, the main focus of this paper. Third, another literature has estimated job losses across sectors and has shown that the contact-intensive sectors suffer more (Barrot et al. 2020; Koren and Pető 2020; Mongey et al. 2020). Like this paper, this literature concerns job losses in the contact-intensive sectors, but does not relate the contact-intensive sectors to environment. Fourth, a literature has related environmental factors and Covid-19 mortality (Bashir et al. 2020; Millett et al. 2020; Wu et al. 2020), but abstracts from emission reductions and economic losses. Fifth, the effects of political attitudes on the response to measures have been studied (Allcott et al. 2020; Beauchamp 2020; Coppins 2020). This line of research does not consider the effects of measures on environment.

The paper is organized as follows. The next section considers a simple model to illustrate the effects of measures on economic activities and emissions. Section 3 discusses the determination of the stringency of a measure. Section 4 studies the role of the stringency of a measure and the size of the contact-intensive sectors in emission reduction. Section 5 provides an empirical analysis, and the last section offers a conclusion.

2 Setup

The economy consists of a continuum of sectors, denoted by $\theta \in [\underline{\theta}, \bar{\theta}]$. Sector θ has $f(\theta)$ workers with $F(\theta) = \int_{\underline{\theta}}^{\theta} f(\theta)d\theta$ and $F(\bar{\theta}) = 1$. Sectors differ only in the degree of person-to-person contacts required in production, and a larger θ requires more contacts. For instance, with $\theta' > \theta$, θ' represents dine-in services in restaurants and θ represents online financial services.

To reduce health risk such as the infection rate and mortality rate in the economy during a pandemic, policymakers implement mitigation measures. A measure and the stringency of the measure are used interchangeably, and both are denoted by m . A larger m means a more severe measure.

The utility of a sector- θ worker depends on net income x , environmental quality q , and public health risk h :

$$u_{\theta}(m) = U(x_{\theta}, q) - h(m). \tag{1}$$

x_{θ} is formulated as³

$$x_{\theta} = y_{\theta} - e_{\theta}(y_{\theta}). \tag{2}$$

y denotes production or gross income of a worker, and production requires energy consumption $e_{\theta}(y)$ in sector θ with $e'_{\theta}(y) > 0$ and $e''_{\theta}(y) > 0$. The cost of energy e is e for

³ It is possible to model x_{θ} as a function of consumption of goods (and services) produced by each sector, rather than net income, as in an earlier version of this paper. However, as the paper focuses on emissions from production, the formulation of x_{θ} in (2) is appropriate and makes the exposition much simpler but does not affect the analysis in an important way. The net-income assumption is equivalent to perfect substitution among goods.

simplicity. Energy consumption e includes any environmental effects resulting from production or income-generating activities, including commuting.

q is modeled as

$$q = Q - E \tag{3}$$

with Q denoting the maximum environmental quality and E denoting the level of emissions that depends on individual energy consumption e . The utility function $U(x, q)$ is assumed to satisfy

$$U_x(x, q) > 0, U_{xx}(x, q) < 0, U_q(x, q) > 0, U_{qq}(x, q) < 0, \tag{4}$$

with subscripts denoting partial derivatives such as $U_x(x, q) = \partial U(x, q) / \partial x$. The signs of the derivatives state that an increase in net income x or environmental quality q increases the utility at a decreasing rate.

As for public health risk h , an increase in the stringency of a measure decreases health risk at a decreasing rate, so $h'(m) < 0$ and $h''(m) > 0$. Unlike x_θ, q and h have no sector subscript θ , meaning that environmental quality q and health risk h are the public good (bad) as opposed to x_θ , the private good. The paper focuses on the effects of mitigation measures on environment, but measures are intended to reduce health risk, and it is included in the model.

A sector- θ worker chooses y to maximize the utility u_θ , taking q and h as given, and the utility-maximizing y , denoted by y_θ , satisfies the FOC (first-order condition)⁴

$$\frac{\partial u_\theta}{\partial y} = U_{\theta x} [1 - e'_\theta(y)] = 0, \tag{5}$$

where the arguments of the utility function (x_θ, q) are, and will be, dropped for simplicity.

Measure m is assumed to limit production activity to $y_\theta(m)$ for $\theta \geq \hat{\theta}$, and a more severe measure reduces $y_\theta(m)$ more, so

$$y_\theta(m) \leq y_\theta, \text{ and } y'_\theta(m) < 0 \text{ for } \theta \geq \hat{\theta} \tag{6}$$

with the equality holding at $\theta = \hat{\theta}$. The measure, however, is assumed to not limit production in sectors $\theta \leq \hat{\theta}$. Sectors with $\theta \in [\hat{\theta}, \bar{\theta}]$ represent the contact-intensive sectors, mentioned in the Introduction. Three comments on the assumption are in order. First, a measure would limit economic activities in almost all sectors, but the assumption above captures the idea that a measure affects different sectors differently. For example, bans on gatherings and nonessential business closures limit severely businesses, such as restaurants and hotels, in the leisure and hospitality industry, as frequently reported by the news media (Pietsch 2020; Suneson 2020) and studied by researchers (Koren and Petö 2020; Mongey et al. 2020). Workers in those sectors are then laid off or cut their work hours. By contrast, education services, teaching and research, can be provided online, and a measure may not seriously affect production of education services. However, even if a measure affects all sectors, it has no effect on the analysis, because all that matters is that the measure reduces

⁴ An individual may consider the effect of his choice of y on E , rather than takes E as given. Since E is the sum of $e(y)$'s chosen by all individuals, y_θ and $e_\theta(y_\theta)$ are determined in a Nash equilibrium. This approach was not taken, as the focus is not on inefficiency of the Nash equilibrium and the presentation becomes more complicated. However, it can be shown that, with additional assumptions, the same result holds.

energy consumption. In this case, the definition of the contact-intensive sectors changes from the sectors affected by a measure to the sectors affected more severely (for example, with more than 50% drop in production).

Second, the reason why a measure limits production does not matter. For instance, bans on gatherings prevent consumers from consuming certain services, decreasing the demand for the services and hence decreasing production of the services. Alternatively, business closures or restrictions directly decrease or shut down production for some sectors.

Third, the assumption does not say that $y_{\theta'} > y_{\theta}$ or $y_{\theta'} < y_{\theta}$ for $\theta' > \theta$, or that y_{θ} with $\theta < \hat{\theta}$ is greater or less than $y_{\theta}(m)$ with $\theta > \hat{\theta}$, similarly for the relationship between $e_{\theta}(y_{\theta})$ and $e_{\theta}(y_{\theta}(m))$. That is, the assumption is about the heterogeneous effects of a measure on sectors, but not about the difference in income or output. A worker in a more-contact-intensive sector may earn a lower or a higher income than a worker in a less-contact-intensive sector. A good portion of contact-intensive sectors such as the leisure and hospitality industry may employ low wage workers, but the health care industry may employ high wage workers although health care can be in general considered a contact-intensive sector.

The level of emissions in the economy is then

$$E(m) = c \left[\int_{\underline{\theta}}^{\hat{\theta}} e_{\theta}(y_{\theta})f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} e_{\theta}(y_{\theta}(m))f(\theta) d\theta \right], \tag{7}$$

where $c > 0$ is the conversion parameter that relates energy use e to emissions E .

3 Mitigation Measures

This section considers the determination of measure m . Given (6), the utility of a sector- θ worker in (1), with measure m , is rewritten as

$$u_{\theta}(m) = \begin{cases} U(y_{\theta} - e_{\theta}(y_{\theta}), Q - E(m)) - h(m) & \text{for } \theta \leq \hat{\theta}, \\ U(y_{\theta}(m) - e_{\theta}(y_{\theta}(m)), Q - E(m)) - h(m) & \text{for } \theta \geq \hat{\theta}. \end{cases} \tag{8}$$

When choosing measure m , policymakers of a jurisdiction are assumed to maximize social welfare of the jurisdiction,

$$W(m) \equiv (1 - \alpha(\hat{\theta})) \int_{\underline{\theta}}^{\hat{\theta}} U(y_{\theta} - e_{\theta}(y_{\theta}), Q - E(m))f(\theta) d\theta + \alpha(\hat{\theta}) \int_{\hat{\theta}}^{\bar{\theta}} U(y_{\theta}(m) - e_{\theta}(y_{\theta}(m)), Q - E(m))f(\theta) d\theta - h(m). \tag{9}$$

$\alpha(\hat{\theta}) \in (0, 1)$ is the weight placed on the contact-intensive sectors. It measures the influence of the contact-intensive sectors, and its interpretation will be discussed below. The size of the contact-intensive sectors equals $1 - F(\hat{\theta})$, and the influence of the contact-intensive sectors is assumed to increase in the size, so

$$\alpha'(\hat{\theta}) < 0. \tag{10}$$

Social welfare $W(m)$ deserves discussion. Policymakers are assumed to care about political support. Political support and hence policy outcomes are determined by the preferences of a median voter in the classical models of democracy (for example, Downs

1957; Meltzer and Richard 1981). However, in modern democracies, political support and policy outcomes depend on other factors such as interest groups and party representation (Kang and Powell 2010; Bonica et al. 2013; Gilens and Page 2014). This discussion is not intended to develop a new model of political support or to advocate or criticize the median voter theory, but to point out that $W(m)$ is a simple way to illustrate the factors, economic loss and health risk, that policymakers consider in formulating mitigation measures. As such, social welfare $W(m)$ is not meant to introduce a social planner or to discuss socially efficient policies unlike the typical connotation the name of $W(m)$, social welfare, carries.

The utility of an individual depends on three factors, income or economic activity x_θ , health risk $h(m)$, and environmental quality q . Policymakers thus in principle would choose m by taking into account the three factors. However, policymakers in practice appear to have focused on economic activity and health risk during the Covid-19 pandemic, not on environmental quality. Whether policymakers consider environmental quality or not is an empirical question, but this paper unfortunately cannot answer the question. However, to the best of my knowledge, it appears from the media reports that policymakers did not consider the effect of measures on environmental quality.⁵ For example, policymakers extended lockdowns due to health concerns (Caspani and Heavey 2020; Winsor et al. 2020), and anti-lockdown debates and protests focused on the impact of lockdowns on jobs and the economy (Los Angeles Times 2020; BBC 2020). The subsequent analysis thus assumes that policymakers do not consider the effects on environmental quality, but for the sake of completeness, the analysis with the other assumption is provided in the “Appendix”. More importantly, measures affect environmental quality, and the analysis relates measures to environmental quality.

The FOC for a maximum of $W(m)$ is

$$W'(m) = \alpha(\hat{\theta}) \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta x} [1 - e'_{\theta}(y_{\theta}(m))] y'_{\theta}(m) f(\theta) d\theta - h'(m) = 0. \tag{11}$$

The FOC does not include the sectors with $\theta \leq \hat{\theta}$, as y_{θ} is independent of m , and the measure has no effect on net income x_{θ} for $\theta \leq \hat{\theta}$ in (8). Since $1 - e'_{\theta}(y_{\theta}) = 0$ by (5) and $y_{\theta}(m) \leq y_{\theta}$ for $\theta \geq \hat{\theta}$ by (6),

$$1 - e'_{\theta}(y_{\theta}(m)) \geq 0 \text{ for } \theta \geq \hat{\theta} \tag{12}$$

due to $e''_{\theta}(y) > 0$. The first term of FOC (11) involving the integral is negative due to (12) along with $y'_{\theta}(m) < 0$. This negative term shows the marginal cost of an increase in the stringency stemming from limiting economic activities and hence decreasing net income for high sector- θ workers with $\theta \geq \hat{\theta}$, namely the contact-intensive sectors. The remaining term represents the marginal benefit resulting from the decrease in health risk $h(m)$. The benefit is common to all workers. However, the costs of increasing the stringency of the measure fall disproportionately on the contact-intensive sectors. This finding is consistent with the literature (Koren and Petö 2020; Mongey et al. 2020) and will be further discussed in the next section. This does not say that the contact-intensive sectors use less energy or more energy than other sectors. Rather, an increase in the stringency of the measure reduces emissions by limiting economic activities in the contact-intensive sectors. For

⁵ An earlier version of this paper assumed that policymakers consider the effect of policies on environmental quality. However, all of my colleagues who read it commented that it is utter nonsense to assume that policymakers consider such effects during the pandemic.

comparative statics results below, social welfare is assumed to be concave and $W''(m) < 0$, so that the second-order condition is satisfied.

Although policymakers did not consider the effect of measure m on environmental quality, the measure affects environmental quality. Using (7),

$$E'(m) = c \int_{\hat{\theta}}^{\bar{\theta}} e'_\theta(y_\theta(m)) y'_\theta(m) f(\theta) d\theta < 0, \tag{13}$$

because $e'_\theta(y) > 0$ and $y'_\theta(m) < 0$ in (6). An increase in the stringency of the measure thus decreases emissions.

4 Size of the Contact-Intensive Sectors

As noted in the previous section, measures affect disproportionately the contact-intensive sectors with $\theta \geq \hat{\theta}$. This section considers the effects of the size of the sectors on the stringency of a measure and emissions.

As proved in the “Appendix”, total differentiation of FOC (11) gives the following result

Proposition 1 $\partial m^*/\partial \hat{\theta} > 0$ (as the size of the contact-intensive sectors increases, the social-welfare maximizing measure becomes less-stringent).

The intuition is that a measure limits economic activities y in the contact-intensive sectors with $\theta \geq \hat{\theta}$, but not in other sectors with $\theta \leq \hat{\theta}$. The loss of the utility of a sector- θ worker resulting from limited economic activities is $y_\theta - e_\theta(y_\theta) - [y_\theta(m) - e_\theta(y_\theta(m))]$ for $\theta \geq \hat{\theta}$. An increase in the stringency increases the loss, because $-[1 - e'_\theta(y_\theta(m))]y'_\theta(m) > 0$. This increase in the loss of the utilities of workers in the contact-intensive sectors represents the increase in the welfare cost of making a measure more stringent. When these workers can exert more influence on policy making, or when $\alpha(\hat{\theta})$ is larger or $\hat{\theta}$ is smaller, it increases the welfare cost of increasing the stringency. Thus, policymakers that care about social welfare have the incentive to reduce the welfare cost and hence to make the measure more lenient.

The proposition will serve as an empirical hypothesis. In particular, the size of the contact-intensive sectors is measured by the fraction of the labor force in certain industries such as the leisure and hospitality industry and the trade and transportation industry. The fraction varies across states, enabling the analysis of the relationship between the stringency of a measure and the fraction of the labor force in the contact-intensive sectors. The stringency of a measure depends on other factors, and the empirical analysis in the next section includes other controls such as hospital capacity and political leaning.

A more stringent measure reduces emissions, as in (13). Since jurisdictions differ in the conversion parameter c and in their initial emission level (before the pandemic or with $m = 0$), the analysis considers the reduction in emissions in percentage terms. To that end, let

$$\begin{aligned} \lambda(\hat{\theta}, m) &\equiv \frac{E(\hat{\theta}, 0) - E(\hat{\theta}, m)}{E(\hat{\theta}, 0)} \\ &= \frac{1}{\int_{\hat{\theta}}^{\bar{\theta}} e_\theta(y_\theta(0)) f(\theta) d\theta} \int_{\hat{\theta}}^{\bar{\theta}} [e_\theta(y_\theta(0)) - e_\theta(y_\theta(m))] f(\theta) d\theta > 0. \end{aligned} \tag{14}$$

The conversion parameter c in the numerator and that in the denominator cancel out. The denominator is the initial level of emissions without a measure, and it is not necessary to separate the contact-intensive sectors from other sectors. The numerator shows the difference between the initial level of emissions and that with measure m . The measure affects only the contact-intensive sectors, and other sectors with $\theta \in [\underline{\theta}, \hat{\theta}]$ do not appear in the numerator. $\lambda(\hat{\theta}, m) > 0$ due to $y'_\theta(m) < 0$ or $y_\theta(m) < y_\theta(0)$, so a larger $\lambda(\hat{\theta}, m)$ means a larger percentage reduction in emissions.

Differentiation of (14) yields

$$\frac{\partial \lambda(\hat{\theta}, m)}{\partial \hat{\theta}} = - \frac{1}{\int_{\underline{\theta}}^{\bar{\theta}} e_\theta(y_\theta(0)) f(\theta) d\theta} [e_{\hat{\theta}}(y_{\hat{\theta}}(0)) - e_{\hat{\theta}}(y_{\hat{\theta}}(m))] f(\hat{\theta}) < 0. \tag{15}$$

The equality uses the Leibniz rule, and the inequality comes from $e'_\theta(y) > 0$ and $y'_\theta(m) < 0$. Likewise,

$$\frac{\partial \lambda(\hat{\theta}, m)}{\partial m} = - \frac{1}{\int_{\underline{\theta}}^{\bar{\theta}} e_\theta(y_\theta(0)) f(\theta) d\theta} \int_{\hat{\theta}}^{\bar{\theta}} e'_\theta(y_\theta(m)) y'_\theta(m) f(\hat{\theta}) > 0. \tag{16}$$

These results can be stated as:

Proposition 2 (i) $\partial \lambda / \partial \hat{\theta} < 0$ and (ii) $\partial \lambda / \partial m > 0$ (an increase in the size of the contact-intensive sectors or the stringency of a measure decreases emissions more in percentage terms).

The intuition is simple. As a measure reduces emissions by limiting economic activities in the contact-intensive sectors, a decrease in $\hat{\theta}$ or an increase in the size of the contact-intensive sectors decreases emissions more but does not affect the initial level of emissions, decreasing emissions more in percentage terms. Since a more stringent measure restricts economic activities more and reduces emissions more but has no effect on the initial level of emissions, it decreases emissions more in percentage terms.

5 Empirical Analysis

The analysis has shown that the reduction in emissions due to a measure during the pandemic depends on the size of the contact-intensive sectors and the severity of the measure, as in Proposition 2. This section tests this result, based on cross-state data. Since the severity is chosen by policymakers and hence is endogenous, as in Proposition 1, IV estimation is also considered.

5.1 Data and Variables

The dependent variable is **CO2reduction**, which is $\lambda(\hat{\theta}, m)$ in (14), the percentage reduction in CO2 emissions in each state. Data comes from Le Qu er  et al. (2020). They estimate the effects of statewide confinement measures on daily changes in CO2 emissions in U.S.

states during the Covid-19 pandemic.⁶ They consider three types of confinement measures, ranging from the scale-1 measure targeting at small groups of residents with possible infection to the scale-2 measure targeting at some cities or regions and to the scale-3 national (statewide) policy targeting all but essential workers. Since the analysis concerns statewide restrictions on economic activities, the last measure is relevant. Data on daily changes in CO₂ emissions (relative to the mean daily CO₂ emissions for 2019) covers the period from January 28, 2020 to April 30, 2020. Although the pattern of changes differs across states, almost all states follow a common pattern. In particular, (i) emissions had changed little until around March 20, 2020, (ii) changed significantly around March 20, 2020, and (iii) remained little changed thereafter until April 30, 2020. The reason for this common pattern is that a national emergency over the pandemic was declared on March 13, 2020, and states started imposing mitigation measures around March 20, 2020. Thus, the effects of measures on emission reduction had occurred mainly after March 20, 2020, and the subsequent analysis uses emission data as of April 30, 2020.

The key independent variable is **measure**. It is the average value of four indexes, compiled by the Kaiser Family Foundation (2020), regarding nonessential business closures, bans on gatherings, school closures, and restaurant closures as of May 8, 2020. The non-essential-business-closure index has seven levels ranging from no restriction to 'all non-essential businesses closed.' The bans-on-gathering index, the school-closure index and the restaurant-closure index have nine levels, five levels, and five levels, respectively. To avoid overrepresenting or underrepresenting a particular index in the calculation of the average value of four indexes, namely **measure**, without evidence, each index is normalized, so that the minimum of each index is set to 1 and the maximum is set to 10. For instance, the first level of the nonessential-business-closure index is 1, the second level is set to 2.5, the third level to 4, the fourth level to 5.5, the fifth level to 7, the sixth level to 8.5, and the maximum is 10. The Kaiser Family Foundation data includes other indexes such as primary election postponement and mandatory quarantine for travelers, but they are not considered, as they do not appear to be directly related to economic activities, the main topic of this paper.

Another key independent variable is the size of the contact-intensive sectors. Two **csector** (contact-intensive sector) variables are considered. **csectora** is the percentage of employment in three industries: leisure/hospitality, trade/transportation, and education/health services. **csectorb** equals the percentage of employment in the leisure/hospitality industry plus 50% of employment in the trade/transportation industry and the education/health services industry. The two variables represent the contact-intensive sectors in a reasonable manner, as the leisure and hospitality industry has been hit hardest, and a typical example of job loss during the recent pandemic includes restaurant and hotel workers, as noted earlier. The trade and transportation industry, including retail stores and airlines and cruise lines, has been also greatly affected. Education and health services had been the main engine of job creation before the Covid-19 pandemic, but have suffered during the pandemic, as a good portion of jobs in the industry require close contacts. At the same time, part of trade, education and health services has been moved to online services, exemplified by online instruction across educational institutions and online retail trades (purchases of goods and services). **csectorb** thus adds 50% of employment in those two industries to employment in the leisure and hospitality industry. Overall, the idea of the

⁶ They also estimate the changes in 69 countries and 30 Chinese provinces.

contact-intensive sectors, reflected in two **csector** variables, is consistent with research findings (Barrot et al. 2020; Koren and Petö 2020; Mongey et al. 2020). Employment data is extracted from the U.S. Bureau of Labor Statistics (2020), and employment equals the seasonally-adjusted number of employees in February 2020, the most recent month before the pandemic.⁷ However, the percentage of employment in **csectora** or **csectorb** had been stable at least for the past 5 years, as will be further discussed below.

The regressions include other control variables that may affect the percentage reduction in CO2 emissions. **drivingCO2** equals the percentage of CO2 emissions resulting from driving in 2019 (before the pandemic). **energycon** equals per capita energy consumption in million Btu, and **urban** measures the percentage of the population living in urban areas. Higher values of these variables are expected to reduce emissions more, because driving is a major source of emissions, more energy consumption results in more emissions, and economic activities are more likely to be concentrated in urban areas. **pollution** equals ‘average exposure of the general public to particulate matter of 2.5 microns or less (PM2.5) measured in micrograms per cubic meter (3-year estimate),’ and **income** is per capita personal income and may represent a broad control. There appears to be no expected sign for each of two variables, but they may have positive effects on emission reduction, as a higher level of pollution may discourage economic activities more during the pandemic, and environmental quality is a normal good. Data on these variables is from Le Quéré et al. (2020), the U.S. Energy Information Administration (2020), Iowa State University (2020), the United Health Foundation (2020), and the U.S. Bureau of Economic Analysis (2020), respectively.

While **CO2reduction** depends on **measure**, **measure** is endogenous, as in Proposition 1. Thus, IV estimation is considered, and three instruments are used for **measure**. **vulnerability** measures the extent to which a state is vulnerable to the Covid-19 pandemic and is based on 20 factors such as social and physical environment and high risk population. It is a score, ranging from 0 to 100, and a higher score means more vulnerability. States that are more vulnerable to the virus are expected to toughen the measures. **hospital** equals the number of hospital beds per 10,000 people, and states with more hospital beds may be more lenient. These two variables are extracted from Barclay and Rodriguez (2020) and the Kaiser Family Foundation (2020), respectively. Democrats and Republicans have different views on measures (Allcott et al. 2020; Beauchamp 2020; Coppins 2020), and political leaning presumably affects the stringency. To control for political leaning and attitudes of states, the governor’s party affiliation and the partisan composition of the legislature of each state are considered. In particular, the National Conference of State Legislatures (2020) determines which party controls a state, and **partisan** equals 1 if a state is controlled by Democrats, and -1 if controlled by Republicans, and zero if divided.

Table 1 presents summary statistics. The dependent variable, **CO2reduction**, ranges from 12.2% in South Carolina to 54.1% in California. The key independent variable, **measure**, is on average 7.8 on a 10-point scale, with 2.4 in South Dakota and 10 in Illinois and New York. The average of each **csector** variable is 0.45 and 0.28, respectively. The mean of **drivingCO2** is 36%, so driving accounts for a significant portion of emissions. **energycon** ranges from 187 million Btu in Rhode Island to 967 in Wyoming. **urban**, **pollution**, **income**, **vulnerability** and **hospital** are on average 74.1, 7.4, 55088, 45.0 and 25.3, respectively. As for **partisan**, 15 and 22 states are controlled by Democrats and Republicans,

⁷ All other variables are also from the most recent data available before the pandemic.

Table 1 Summary statistics

| Variables | No. of observations | Mean | SD | Minimum | Maximum |
|---------------|---------------------|-----------|-----------|-----------|-----------|
| CO2reduction | 50 | 37.88732 | 8.954468 | 12.22 | 54.100951 |
| measure | 51 | 7.792279 | 1.773171 | 2.40625 | 10 |
| csectora | 51 | 0.4529698 | 0.0351703 | 0.3051375 | 0.5324266 |
| csectorb | 51 | 0.282507 | 0.0259567 | 0.2035079 | 0.3904508 |
| drivingco2 | 51 | 0.3586852 | 0.1151699 | .124 | 0.576 |
| energycon | 51 | 361.9412 | 183.5807 | 187 | 967 |
| urban | 51 | 74.10784 | 14.88548 | 38.7 | 100 |
| pollution | 51 | 7.413725 | 1.457535 | 4.4 | 12.8 |
| income | 51 | 55,088.41 | 9675.347 | 39,368 | 84538 |
| vulnerability | 50 | 45.02 | 10.90469 | 17.2 | 74.1 |
| hospital | 51 | 25.32353 | 6.730337 | 15.1 | 46.7 |
| partisan | 50 | - 0.14 | 0.8573809 | - 1 | 1 |
| csectora5yr | 51 | 0.4523536 | 0.0352567 | 0.307767 | 0.5490294 |
| csectorb5yr | 51 | 0.2813026 | 0.0270094 | 0.2028069 | 0.406225 |
| measurealter | 51 | 3.387255 | 0.5880343 | 1.25 | 4 |

respectively, and 13 states are divided. **vulnerability** or **partisan** is not available for D.C., and **CO2reduction** is not available for Colorado. The remaining variables, **csectora5yr**, **csectorb5yr** and **measurealter**, will be used for robustness checks and will be explained below.

5.2 Regression Results

Table 2 shows OLS regression results as a benchmark. The table includes four specifications, depending on which **csector** variable is used and on whether or not additional controls are added to two key independent variables, **measure** and **csector** variables. The variables of interest are **measure** and **csectora** or **csectorb**. The coefficients of the variables are all positive, so jurisdictions with a more stringent measure or a larger contact-intensive sector experience a larger percentage reduction in emissions, confirming the result in Proposition 2. The coefficients of **measure** are significant at the 1% level, and those of **csectora** are significant at the 5% level in (i) and (ii), and those of **csectorb** are significant at the 1% level in (iii) and (iv). Additional controls, except **urban**, have positive effects on the percentage reduction in emissions, as expected. Thus, emissions fall more in states with higher levels of emissions from driving, more energy consumption, higher levels of pollution, and higher incomes. The coefficients of these variables are significant at the 5% or 1% level, except that the coefficient of **income** is not significant. The comparison between (i) and (ii) or the comparison between (iii) and (iv) reveals that additional controls overall do not affect much the role of **measure** or **csector** variables in explaining the percentage reduction in emissions.

measure obviously reduces emissions by limiting economic activities, but the question concerns the extent to which **measure** explains **CO2reduction**. The standard deviation of **CO2reduction** is 8.95, and that of **measure** equals 1.77 from Table 1. Since the average

Table 2 OLS regression results

| | (i) | (ii) | (iii) | (iv) |
|-----------------|----------------------------|----------------------------|---------------------------|-----------------------------|
| measure | 2.580565*** (0.5591841) | 2.052265*** (0.4505527) | 2.61173*** (0.5549554) | 2.087006*** (0.4612909) |
| csectora | 57.949** (28.80624) | 63.29935** (29.46499) | | |
| csectorb | | | 88.08037*** (27.73998) | 85.60787*** (31.2706) |
| drivingCO2 | | 40.56943*** (12.86881) | | 38.2253*** (13.29057) |
| energycon | | 0.0161516** (0.0065157) | | 0.014568** (0.0072703) |
| urban | | - 0.010938 (0.0667565) | | - 0.0432354 (0.0673018) |
| pollution | | 1.784172*** (0.622245) | | 1.749415*** (0.5724822) |
| income | | 0.0001026 (0.0001439) | | 0.0001351 (0.0001455) |
| constant | - 8.478572 (15.04224) | - 45.36403** (18.29636) | - 7.336215 (10.50401) | - 38.84338*** (13.99415) |
| <i>N</i> | 50 | 50 | 50 | 50 |
| <i>F</i> | 11.27 | 10.93 | 12.79 | 11.09 |
| Prob > <i>F</i> | 0.0001 | 0.0000 | 0.0000 | 0.0000 |
| R-squared | 0.2987 | 0.4887 | 0.3129 | 0.4870 |

The numbers in parentheses in all regressions and all tables are robust errors

***, ** and * in all regressions and all tables indicate statistical significance at the 1%, 5% and 10%, respectively

of the four coefficients of **measure** is about 2.3 across four specifications in Table 2, a one-standard-deviation increase in **measure** increases **CO2reduction** by $2.3 \times 1.77 = 4.07$, explaining about 45% ($= 4.07/8.95 = 0.45$) of the standard deviation of **CO2reduction**. The explanatory power of **csector** variables can be considered in a manner analogous to that of **measure**. The standard deviation of **csectora** equals 0.035. Since the average of two coefficients of **csectora** in specifications (i) and (ii) is about 60, a one-standard-deviation increase in **csectora** increases **CO2reduction** by $60 \times 0.035 = 2.1$, explaining about 23% ($= 2.1/8.95 = 0.23$) of the standard deviation of **CO2reduction**. Analogously, a one-standard-deviation increase in **csectorb** explains about 25% of the standard deviation of **CO2reduction**.⁸

⁸ The standard deviations of **csectorb** is 0.026, and the coefficients of **csectorb** are on average about 87 in specifications (iii) and (iv). Thus, a one-standard-deviation increase in **csectorb** explains about $87 \times 0.026/8.95 = 0.25 = 25\%$ of the standard deviation of **CO2reduction**.

Table 3 Regression results with **csectora5yr** and **csectorb5yr**

| | (i) | (ii) | (iii) | (iv) |
|-----------------|---------------------------|----------------------------|---------------------------|-----------------------------|
| measure | 2.56923*** (0.5578172) | 2.059925*** (0.4473105) | 2.58671*** (0.5534009) | 2.084091*** (0.4580055) |
| csectora5yr | 54.46989** (26.51683) | 58.39911** (28.40208) | | |
| csectorb5yr | | | 79.37035*** (26.19922) | 76.10499** (30.10278) |
| drivingCO2 | | 40.54768*** (13.10111) | | 38.87149*** (13.34683) |
| energycon | | 0.0163956** (0.0067266) | | 0.0150745** (0.0074438) |
| urban | | - 0.008959 (0.0687597) | | - 0.0379541 (0.0678989) |
| pollution | | 1.753435*** (0.6234928) | | 1.706978*** (0.567364) |
| income | | 0.0000975 (0.000144) | | 0.0001256 (0.0001455) |
| constant | - 6.772395 (14.18937) | - 42.87514** (17.97345) | - 4.57543 (10.16302) | - 36.00629*** (13.74689) |
| <i>N</i> | 50 | 50 | 50 | 50 |
| <i>F</i> | 11.11 | 10.59 | 12.19 | 10.74 |
| Prob > <i>F</i> | 0.0001 | 0.0000 | 0.0001 | 0.0000 |
| R-squared | 0.2933 | 0.4804 | 0.3053 | 0.4797 |

5.3 Robustness Checks

This section considers a few robustness checks. First, **csectora** and **csectorb** represent the percentage of employment in the relevant industries in February 2020. Given the importance of **csector** variables, this section considers the average of percentage of employment for the past 5 years. That is, **csectora5yr** equals the 5-year average of **csectora** for 2015 through 2019, and similarly for **csectorb5yr**. Regression results with **csectora5yr** and **csectorb5yr** are presented in Table 3. The results in the table differ little from those in Table 2. In particular, the coefficients of **measure** and **csector** variables remain little affected, so **measure** and **csector** variables continue to have positive and significant effects on the dependent variable, **CO2reduction**. The coefficients of other control variables also remain little affected.

Second, as in Table 1, **CO2reduction** varies considerably across states, ranging from 12.2 to 54.1%. To eliminate the possibility that a few states with extreme values of **CO2reduction** unduly affect regression results, those states with extreme values (more than two standard deviations away from the mean) are eliminated in Table 4. Since the mean of **CO2reduction** equals 37.89 and the standard deviation equals 8.95, no state has **CO2reduction** exceeding $55.79 = 37.89 + 2 \times 8.95$, two standard deviations above the mean, given that the maximum of **CO2reduction** is 54.1. However, **CO2reduction** is less than $19.99 = 37.89 - 2 \times 8.95$, two standard deviations below the mean, for three states, Iowa,

Table 4 Regression results without outliers

| | (i) | (ii) | (iii) | (iv) |
|-----------------|---------------------------|-----------------------------|----------------------------|-----------------------------|
| measure | 2.13124*** (0.5175619) | 1.945532*** (0.4205093) | 2.186463*** (0.5210458) | 1.986129*** (0.420779) |
| csectora | 41.86357* (24.01916) | 40.99654** (19.03765) | | |
| csectorb | | | 70.25909*** (25.3269) | 61.0625*** (21.36089) |
| drivingCO2 | | 48.32888*** (7.40334) | | 46.81764*** (6.96585) |
| energycon | | 0.0209304*** (0.0063342) | | 0.0198856*** (0.0066808) |
| urban | | - 0.0111317 (0.0588843) | | - 0.0357502 (0.0595987) |
| pollution | | 1.554829*** (0.5797073) | | 1.577481*** (0.5401421) |
| income | | 0.0000268 (0.0000948) | | 0.0000505 (0.0000967) |
| constant | 3.425166 (13.10715) | - 31.9686** (13.51083) | 2.105026 (9.695655) | - 29.68628*** (11.33797) |
| <i>N</i> | 47 | 47 | 47 | 47 |
| <i>F</i> | 8.57 | 11.86 | 9.92 | 12.44 |
| Prob > <i>F</i> | 0.0007 | 0.0000 | 0.0003 | 0.0000 |
| R-squared | 0.2891 | 0.6185 | 0.3123 | 0.6250 |

North Dakota and South Carolina. As shown in Table 4, the elimination of three states does not affect regression results in Table 2 in an important way. In particular, the explanatory power of the key independent variables, **measure** and **csector** variables, remains almost the same, except that the coefficient of **csectora** becomes significant at the 10% level in (i), rather than at the 5% level in Table 2. The effects of other control variables on **CO2reduction** remain qualitatively the same.

Third, **measure** in Table 2 is the average of four indexes, and each index consists of a number of levels. For example, the nonessential-business-closure index consists of seven levels while the restaurant-closure index consists of five levels. Each level represents a severity of a measure, but the difference between one level and another may be ambiguous or may be small in some cases. For instance, in the case of the nonessential-business-closure index, level 5 refers to ‘some nonessential businesses permitted to reopen with reduced capacity,’ and level 6 refers to ‘some nonessential businesses closed.’ These two levels may not differ much in terms of the severity of restrictions on businesses, and a new nonessential-business-closure index is considered by regrouping seven levels into four levels. Likewise, a new index for each of three other indexes regroups the existing number of levels into four levels. This uniform number of levels, namely four levels, across the indexes also obviates the need to normalize the minimum of each index to 1 and the maximum to 10. The average of four new indexes is named **measurealter**, meaning an alternative **measure**. Table 5 shows regression results with **measurealter**. The coefficients

Table 5 Regression results with **measurealter**

| | (i) | (ii) | (iii) | (iv) |
|-----------------|---------------------------|-----------------------------|--------------------------|-----------------------------|
| measurealter | 7.232616*** (1.686756) | 5.443531*** (1.343075) | 7.17079*** (1.671431) | 5.344354*** (1.40712) |
| csectora | 60.24973** (28.65554) | 66.46831** (29.40079) | | |
| csectorb | | | 84.75921*** (28.0986) | 84.06921** (33.46773) |
| drivingCO2 | | 39.78771*** (13.1406) | | 37.59302*** (13.6278) |
| energycon | | 0.0151207** (0.0069977) | | 0.0132072* (0.0078973) |
| urban | | - 0.013514 (0.0686947) | | - 0.0436481 (0.0710582) |
| pollution | | 1.898795*** (0.6672995) | | 1.840653*** (0.631972) |
| income | | 0.0001344 (0.0001482) | | 0.0001655 (0.0001528) |
| constant | - 13.89177 (15.38315) | - 50.98678*** (19.06149) | - 10.31518 (11.10973) | - 41.83369*** (15.49473) |
| <i>N</i> | 50 | 50 | 50 | 50 |
| <i>F</i> | 10.44 | 9.87 | 11.68 | 9.74 |
| Prob > <i>F</i> | 0.0002 | 0.0000 | 0.0001 | 0.0000 |
| R-squared | 0.2605 | 0.4653 | 0.2660 | 0.4568 |

of **measurealter** are still positive and significant at the 1% level. The main difference from the results in Table 2 is that the coefficients of **measurealter** are larger than those of **measure** in Table 2. This difference comes from the fact that **measurealter** ranges from 1 to 4 while **measure** ranges from 1 to 10. However, this difference has no qualitative effect on the explanatory power of **measurealter**. Simple calculation can show that a one-standard-deviation increase in **measurealter** increases **CO2reduction** by $6.2 \times 0.59 = 3.66$, explaining about 41% ($= 3.66/8.95 = 0.41$) of the standard deviation of **CO2reduction**. In addition, the substitution of **measurealter** for **measure** affects little the role of **csector** variables in explaining the dependent variable.

5.4 IV Estimation Results

As discussed in Sect. 3, the stringency of a measure, **measure**, is determined by policymakers and is endogenous. Table 6 thus presents IV estimation results by using three variables, **vulnerability**, **hospital** and **partisan**, as instruments for **measure**. Comparing Tables 2 and 6, IV estimation results differ little from OLS results qualitatively in the sense that two key variables, **measure** and **csectora** or **csectorb**, continue to have positive effects on the percentage reduction in emissions and continue to be significant. In particular, the coefficients of **measure** and **csector** variables are significant at 1% level in all specifications, except that the coefficient of **csectora** is significant at the 5% level in

Table 6 IV estimation results

| | (i) | (ii) | (iii) | (iv) |
|--|----------------------------|-----------------------------|----------------------------|-----------------------------|
| measure | 4.165217*** (0.9190636) | 3.561031*** (0.9071167) | 4.025196*** (0.8802389) | 3.455272*** (0.8688946) |
| csectora | 85.80079*** (34.87017) | 87.80737** (36.45336) | | |
| csectorb | | | 108.4632*** (30.44439) | 96.80585*** (32.20672) |
| drivingCO2 | | 42.00471*** (12.46641) | | 38.94026*** (12.99128) |
| energycon | | 0.0223346*** (0.0071323) | | 0.019367*** (0.0072716) |
| urban | | − 0.0064525 (0.0579581) | | − 0.0490539 (0.0607414) |
| pollution | | 1.422599** (0.7191335) | | 1.485874** (0.6326718) |
| income | | − 0.0000272 (0.0001299) | | 0.0000592 (0.00014) |
| constant | − 33.6168* (17.66505) | − 61.68385*** (21.69242) | − 24.19059* (12.71093) | − 48.14237*** (15.49203) |
| <i>N</i> | 49 | 49 | 49 | 49 |
| <i>F</i> | 12.81 | 9.20 | 12.80 | 9.42 |
| Prob > <i>F</i> | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| R-squared | 0.2096 | 0.4332 | 0.2369 | 0.4336 |
| Underidentification test, Chi-sq(3) P-val (Kleibergen-Paap rk LM statistic) | 0.0005 | 0.0193 | 0.0002 | 0.0166 |
| Cragg–Donald Wald F statistic | 15.654 | 9.261 | 18.269 | 10.133 |
| Kleibergen–Paap Wald F statistic | 18.312 | 8.856 | 19.604 | 8.662 |
| Stock–Yogo critical values (10%) | 22.30 | 22.30 | 22.30 | 22.30 |
| Stock–Yogo critical values (15%) | 12.83 | 12.83 | 12.83 | 12.83 |
| Stock–Yogo critical values (20%) | 9.54 | 9.54 | 9.54 | 9.54 |
| Stock–Yogo critical values (25%) | 7.80 | 7.80 | 7.80 | 7.80 |
| Hansen J statistic : Chi-sq(2) P-val (Overidentification test of instruments) | 0.9674 | 0.6588 | 0.8642 | 0.6458 |

specification (ii). Thus, even if the endogeneity of **measure** is taken into account, **measure** and **csector** variables have significant explanatory power, as predicted by the model. The magnitudes of the Wald F statistic indicate that instruments do not appear to be weak. Due to three instruments, the model is overidentified, and the *p*-values for the Hansen-J statistic show that instruments do not appear to be endogenous.

Table 7 shows first-stage regression results with **measure** as the dependent variable. The key independent variable is the size of the contact-intensive sectors. The coefficients of **csectora** and **csectorb** are negative in all specifications, so measures become less stringent as the size of the contact-intensive sectors increases, confirming the result in Proposition 1.

Table 7 First-stage regression results

| | (i) | (ii) | (iii) | (iv) |
|----------------------------------|------------------------------|------------------------------|-------------------------------|-----------------------------|
| <i>csectora</i> | - 13.51271* (7.252275) | - 15.7362* (8.449782) | | |
| <i>csectorb</i> | | | - 22.8657*** (5.900861) | - 21.96542*** (8.108359) |
| <i>vulnerability</i> | 0.0436566** (0.0198858) | 0.0609704*** (0.0236181) | 0.0514102*** (0.0193664) | 0.0655058*** (0.0236116) |
| <i>hospital</i> | - 0.0965627** (0.0405775) | - 0.1064771** (0.0502914) | - 0.1030865*** (0.0391267) | - 0.106974* (0.0511628) |
| <i>partisan</i> | 1.192177*** (0.2536144) | 0.9449867*** (0.2967671) | 1.243*** (0.2487065) | 0.99833*** (0.2939105) |
| <i>drivingCO2</i> | | - 3.441048 (2.863046) | | - 2.723933 (2.993249) |
| <i>energycon</i> | | - 0.0028418 (0.0024463) | | -0.0023549 (0.0021995) |
| <i>urban</i> | | - 0.0136239 (0.0189131) | | - 0.0032224 (0.0216707) |
| <i>pollution</i> | | - 0.009311 (0.2339173) | | - 0.0448913 (0.2251928) |
| <i>income</i> | | 0.0000615* (0.0000327) | | 0.0000446 (0.0000322) |
| <i>constant</i> | 14.5737*** (3.397144) | 15.01492*** (5.118562) | 14.72574*** (1.932979) | 13.87237*** (4.042135) |
| <i>N</i> | 49 | 49 | 49 | 49 |
| <i>F</i> | 18.31 | 8.86 | 19.60 | 8.66 |
| (F test of excluded instruments) | | | | |
| Prob > <i>F</i> | 0.0000 | 0.0001 | 0.0000 | 0.0002 |

The coefficients of ***csectora*** are significant at the 10% level in specifications (i) and (ii), and the coefficients of ***csectorb*** are significant at the 1% level in (iii) and (iv). ***vulnerability*** has positive effects on the stringency of a measure with its significance at the 5% level in (i) and at the 1% level in other specifications, as policymakers in more vulnerable states are expected to increase the stringency. The coefficient of ***hospital*** is negative and significant at the 1% level in (iii) and at the 5% level in other specifications, so a measure is less stringent in medically better-prepared states. The coefficient of ***partisan*** is positive and significant at the 1% level in all specifications. Measures thus tend to be more stringent in Democrat-controlled states. This result is consistent with the findings that Democrats care about health risks more than Republicans (Allcott et al. 2020; Beauchamp 2020; Coppins 2020).

6 Conclusion

The paper has mainly studied the effects of mitigation measures on emissions during a pandemic. The analysis has shown that emissions fall more as the stringency of a measure or the size of the contact-intensive sectors increases. Available empirical evidence shows that states with a more stringent measure or a larger share of the contact-intensive sectors experience larger emission reduction.

The paper also has considered the determination of the stringency of a measure by policymakers. It is reasonable to assume that policymakers consider health benefits and economic losses when determining the stringency. However, since measures limit economic activities and hence reduce emissions, and since society cares about environmental quality, a natural question concerns if policymakers also consider environmental benefits resulting from an increase in the stringency of a measure. The question is empirical, but there is no data to help in answering the question. However, as discussed in Sect. 3, it appears that policymakers did not intend to reduce emissions when they imposed restrictions on economic activities during the Covid-19 pandemic. This does not mean that policymakers should not consider environmental benefits. In fact, the recent pandemic recovery plan of the European Commission promotes green energy (Krukowska and Lombrana 2020; Oroschakoff and Hernandez-Morales 2020). In addition, environmental groups have learned the environmental benefits from the Covid-19 related measures and have planned to influence environmental policies, including mitigation measures, in case of another pandemic or outbreak. It is thus likely that environmental benefits play a role in shaping the stringency of a mitigation measure in the future.

In the event that policymakers consider environmental benefits in formulating a measure, the analysis has identified the size of the contact-intensive sectors as a key determinant of the stringency of a measure. In particular, since measures affect disproportionately the contact-intensive sectors, the size of the contact-intensive sectors determines the magnitude of economic losses and the extent of environmental benefits as well. An optimal stringency would balance the economic losses and environmental benefits, along with health benefits. As a result, the relationship between the size of the contact-intensive sectors and the stringency would be in general complicated and depend on other parameters of the economy such as the preferences for environmental quality and the shape of the energy-consumption function, as in the “Appendix”. The role of environmental benefits in mitigation policies appears to warrant more research, and I hope that the analysis of the contact-intensive sectors in this paper provides a framework for future research.

The discussion above has a larger implication. Much of the literature on the Covid-19 pandemic has focused on the effects of the pandemic on health outcomes such as infections and mortality rates, or economic outcomes such as job losses and income inequality, or environmental outcomes such as emissions and conservation attitudes. However, little has been studied about the determinants and policy making of mitigation measures. To the extent that citizens of a jurisdiction care about these outcomes, policymakers of the jurisdiction would consider them in formulating mitigation measures. A political process also plays an important role in making any policies and should be considered to understand the determinants of mitigation measures. In addition, even

if policymakers of a jurisdiction consider all relevant factors in determining mitigation measures for the benefit of the jurisdiction, they are unlikely to consider the well-being of other jurisdictions and jurisdictional mitigation measures will create externalities, as individuals move between jurisdictions and the virus can spread from one jurisdiction to another. As a result, jurisdictional measures will be inefficient, and this inefficiency calls for more cooperation between jurisdictions to achieve efficiency. These issues surrounding mitigation measures deserve more attention, and I hope that the analysis in this paper contributes to understanding mitigation policies.

Appendix

Proof of Proposition 1 Given the concavity of $W(m)$, the sign of $\partial m^* / \partial \hat{\theta}$ is identical to that of

$$\begin{aligned} \frac{\partial m^*}{\partial \hat{\theta}} &\cong \frac{\partial W'(m)}{\partial \hat{\theta}} \\ &= \alpha'(\hat{\theta}) \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta x} [1 - e'_{\theta}(y_{\theta}(m))] y'_{\theta}(m) f(\theta) d\theta \\ &\quad - \alpha(\hat{\theta}) U_{\hat{\theta} x} [1 - e'_{\hat{\theta}}(y_{\hat{\theta}}(m))] y'_{\hat{\theta}}(m) f(\hat{\theta}) \\ &= \alpha'(\hat{\theta}) \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta x} [1 - e'_{\theta}(y_{\theta}(m))] y'_{\theta}(m) f(\theta) d\theta > 0. \end{aligned}$$

The first equality comes from simple differentiation by using the Leibniz rule. The second equality follows from $1 - e'_{\theta}(y_{\theta}(m)) = 0$ at $\theta = \hat{\theta}$ from (12). The inequality follows because $1 - e'_{\theta}(y_{\theta}(m)) \geq 0$ and $y'_{\theta}(m) < 0$ for $\theta \geq \hat{\theta}$ from (12) and $\alpha'(\hat{\theta}) < 0$ from (10).

When the effect of a measure on environmental quality is considered

Proposition 2 remains intact, and Proposition 1 is modified. FOC (11) is modified as

$$\begin{aligned} W'(m) &= \alpha(\hat{\theta}) \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta x} [1 - e'_{\theta}(y_{\theta}(m))] y'_{\theta}(m) f(\theta) d\theta \\ &\quad - \left[(1 - \alpha(\hat{\theta})) \int_{\underline{\theta}}^{\hat{\theta}} U_{\theta q} f(\theta) d\theta + \alpha(\hat{\theta}) \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta q} f(\theta) d\theta \right] E'(m) - h'(m) = 0. \end{aligned}$$

As in the proof of Proposition 1, the sign of $\partial m^* / \partial \hat{\theta}$ is identical to that of

$$\begin{aligned}
\frac{\partial m^*}{\partial \hat{\theta}} &\cong \frac{\partial W'(m)}{\partial \hat{\theta}} \\
&= \alpha'(\hat{\theta}) \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta x} [1 - e'_{\theta}(y_{\theta}(m))] y'_{\theta}(m) f(\theta) d\theta \\
&\quad - \alpha(\hat{\theta}) U_{\hat{\theta} x} [1 - e'_{\theta}(y_{\hat{\theta}}(m))] y'_{\hat{\theta}}(m) f(\hat{\theta}) \\
&\quad + \alpha'(\hat{\theta}) \left[\int_{\underline{\theta}}^{\hat{\theta}} U_{\theta q} f(\theta) d\theta - \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta q} f(\theta) d\theta \right] E'(m) \\
&\quad + \left[(1 - \alpha(\hat{\theta})) \int_{\underline{\theta}}^{\hat{\theta}} U_{\theta q} f(\theta) d\theta + \alpha(\hat{\theta}) \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta q} f(\theta) d\theta \right] c e'_{\theta}(y_{\hat{\theta}}(m)) y'_{\hat{\theta}}(m) f(\hat{\theta}) \\
&= \alpha'(\hat{\theta}) \left\{ \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta x} [1 - e'_{\theta}(y_{\theta}(m))] y'_{\theta}(m) f(\theta) d\theta \right. \\
&\quad \left. + \left[\int_{\underline{\theta}}^{\hat{\theta}} U_{\theta q} f(\theta) d\theta - \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta q} f(\theta) d\theta \right] E'(m) \right\} \\
&\quad + \left[(1 - \alpha(\hat{\theta})) \int_{\underline{\theta}}^{\hat{\theta}} U_{\theta q} f(\theta) d\theta + \alpha(\hat{\theta}) \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta q} f(\theta) d\theta \right] c e'_{\theta}(y_{\hat{\theta}}(m)) y'_{\hat{\theta}}(m) f(\hat{\theta}) \\
&= \frac{\alpha'(\hat{\theta}) E'(m)}{\alpha(\hat{\theta})} \left\{ \int_{\underline{\theta}}^{\hat{\theta}} U_{\theta q} f(\theta) d\theta + \frac{h'(m)}{E'(m)} \right\} \\
&\quad + \left[(1 - \alpha(\hat{\theta})) \int_{\underline{\theta}}^{\hat{\theta}} U_{\theta q} f(\theta) d\theta + \alpha(\hat{\theta}) \int_{\hat{\theta}}^{\bar{\theta}} U_{\theta q} f(\theta) d\theta \right] c e'_{\theta}(y_{\hat{\theta}}(m)) y'_{\hat{\theta}}(m) f(\hat{\theta})
\end{aligned}$$

The first equality comes from simple differentiation. The second equality follows from $1 - e'_{\theta}(y_{\theta}(m)) = 0$ at $\theta = \hat{\theta}$ from (12) and from rearrangement of terms. The third equality follows from substitution of $\int_{\hat{\theta}}^{\bar{\theta}} U_{\theta x} [1 - e'_{\theta}(y_{\theta}(m))] y'_{\theta}(m) f(\theta) d\theta$ from the FOC, $W'(m) = 0$. The first line after the last equality is positive due to $\alpha'(\hat{\theta}) < 0$, $E'(m) < 0$ and $h'(m) < 0$. The second line is negative due to $e'_{\theta}(y_{\hat{\theta}}(m)) > 0$ and $y'_{\hat{\theta}}(m) < 0$. As a result, the sign of $\partial m^* / \partial \hat{\theta}$ cannot be determined without further assumptions and becomes an empirical question. The first-stage regression results in Table 7 show that an increase in the size of the contact-intensive sectors decreases the stringency of a measure, so $\partial m^* / \partial \hat{\theta} > 0$. \square

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