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Pandemics and support for mitigation measures

Kangoh Lee[1]

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Abstract
Measures reduce health risk but limit economic activities and affect disproportionately the contact-intensive sectors whose economic activities involve more person-to-person interactions. The analysis shows that the size of the contact-intensive sectors shapes the stringency of measures due to the economic interactions between the contact-intensive sectors and other sectors although they constitute a minority of the labor force. Exploiting variation in measures and economic conditions across states, an empirical analysis shows that the number of contact-intensive workers has a negative effect on the stringency of measures.

Keywords Pandemics · Mitigation measures · Support

JEL Classification I1 · R1 · H1

1 Introduction

During the Covid-19 pandemic, policymakers have implemented various containment measures. Such measures are intended to reduce health risks but also result in economic losses. A question concerns the severity of a measure that balances the health benefit and the economic loss, the topic that has recently received a good deal of attention (for example, Alvarez et al. 2020; Eichenbaum et al. 2020; Jones et al. 2020). This paper attempts to contribute to this literature by studying the heterogeneous utility effects of a measure between the contact-intensive sectors and other sectors, a topic that has been rarely considered to the best of my knowledge, although heterogeneous job-loss effects have been studied (Barrot et al. 2020; Mongey et al. 2020).

✉ Kangoh Lee
klee@sdsu.edu

[1] Department of Economics, San Diego State University, 5500 Campanile Drive, San Diego, CA 92182-4485, USA

In the model, a jurisdiction/state consists of two sectors, the contact-intensive sector such as the leisure and hospitality industry, called sector *a*, whose economic activities involve more person-to-person interactions and are affected more by a mitigation measure, and the other sector such as online businesses, called sector *b*, that is less affected. A worker produces in one sector but consumes both good (representing goods and service) *A*, produced by sector *a*, and good *B*, produced by sector *b*. A measure such as a partial business closure (or partial opening with 25% capacity) and social distancing limits consumption of good *A*. The measure also decreases production efficiency in both sectors, for example, as production may require coordination among workers and the measure may make such coordination difficult. A measure is assumed to affect sector-*a*'s production more. The economic loss from limited consumption affects both sector-*a* workers and sector-*b* workers, as they consume both goods. The economic loss, from limited production due to the lower consumption of good *A* and the decrease in production efficiency, affects disproportionately sector-*a* workers. The measure mitigates health risks workers are exposed to and benefits them, but benefits sector-*a* workers more. Sector-*a* workers and sector-*b* workers thus differ in their preferred stringency.

Taking the argument above one step further, the size of sector *a* can be related to the stringency of a measure. Sector-*b* workers benefit from a larger share of sector *a*, as it decreases the price of good *A* they consume but does not directly affect their income. As a result, when the share of sector *a* is larger, sector-*b* workers want to reduce the stringency to enjoy the benefit of the lower price. This does not say that sector-*b* workers prefer a less-stringent measure than sector-*a* workers. Rather, it is about the change in the preferences for the stringency of each sector in response to a change in the size of sector *a*, which helps in establishing the empirical hypothesis below. Thus, if a majority chooses a measure or a policymaker reflects the preferences of the majority when choosing it, the measure becomes less stringent as the size of sector *a* increases although sector-*a* workers constitute a minority of the labor force, a reasonable assumption in modern developed economies, as discussed below. That is, measures tend to be less stringent in states with a larger share of sector *a*. This result serves as the hypothesis in the empirical analysis.

This paper is related to a large number of recent papers on the Covid-19 pandemic. First, much of the literature has considered the infection externalities that individuals impose on others. The key result is that a severe and early measure reduces the mortality rate at the cost of a severe economic downturn (Alvarez et al. 2020; Atkeson 2020; Bethune and Korinek 2020; Jones et al. 2020; Eichenbaum et al. 2020). This literature, like this paper, studies the health-benefit and economic-loss trade-off, but does not consider the heterogeneous utility effects between two sectors and political support for measures.

Second, a number of papers consider multi-sector models. Barrot et al. (2020) estimate the effects of social distancing on GDP by taking into account the relationships between sectors. Koren and Petö (2020) study which jobs are most affected by measures such as social distancing. Mongey et al. (2020) find that low-work-from-home and high-physical-contacts jobs are more vulnerable to various measures. These papers focus on the heterogeneous job-loss effects across sectors, rather than comparing the utilities of workers across sectors.

Another literature considers the effects of political leaning on the response to measures. Allcott et al. (2020) find that Democrats and Republicans differ in social distancing behavior. Likewise, Democrats and Republicans differ in their views of the importance of health risks and economic losses (Beauchamp 2020; Coppins (2020)). This literature, like this paper, studies a political aspect of measures, but does not consider the heterogeneous utility effects of measures.

The next section considers a simple model. Section 3 analyzes the heterogeneous utility effects and the determination of the stringency of a measure. Section 4 provides an empirical analysis, and the last section offers a conclusion.

2 Setup

2.1 Economic activities and health risks

There are two goods (representing both goods and services), A and B. Good A (B) is produced by sector a (b). There is a continuum of workers with mass 1. A worker produces in one sector but consumes both good A and good B. Sector i employs n_i identical workers, $i = a, b$, so n_i is the proportion of workers in sector i.

θ denotes the severity of a (mitigation) measure under consideration. The question concerns how the choice of the severity θ in a jurisdiction depends on the economic and health conditions of the jurisdiction, enabling an empirical analysis of the relationship between the severity and the conditions across jurisdictions. As such, it should be stressed from the outset that this paper does not study the effect of introducing a measure.

The utility of a worker is written as

$$v_i(\theta) \equiv u_i(\theta) - h_i(\theta), i = a, b,$$

$$u_i \equiv (A_i)^{\alpha} (B_i)^{\beta} - \ell_i, \alpha + \beta = 1. \tag{1}$$

u_i represents the economic utility from a sector-i worker's economic activities, consumption and labor supply. $h_i(\theta)$ represents the health risk for a sector-i worker. The worker enjoys the utility from the consumption of A and B, denoted by A_i and B_i, respectively. A represents goods and services whose consumption involves more person-to-person interactions and is affected more by a measure, and B represents goods whose consumption is less affected. For instance, A represents dine-in services in a restaurant, and B may represent online purchase of goods. The last term of u_i, $-\ell_i$, is the disutiliy of labor supply and will be discussed below.

Consumption of A poses more health risk due to more person-to-person contacts than that of B, and a measure is assumed to limit consumption of A to $A(\theta)$, so

$$A_i = A(\theta), i = a, b. \tag{2}$$

In reality, almost all sectors are affected by a measure to some degrees, but (2) captures the idea that some sectors are more affected than others. A more severe measure is assumed to limit consumption of A more, so

$$A'(\theta) < 0. \tag{3}$$

Health risk from consumption of A should be included in the utility function, but it does not affect the analysis qualitatively and is relegated to the appendix to avoid cluttering up notations.

An increase in the stringency of a measure is assumed to decrease the health risk $h_i(\theta)$, but more for sector-a workers, so

$$h_a'(\theta) \leq h_b'(\theta) < 0. \tag{4}$$

2.2 Labor supply and income

A sector-i worker supplies ℓ_i units of labor. With measure θ, the effective units of labor supply become[1]

$$L_i(\theta) \equiv \ell_i - \phi_i(\theta). \tag{5}$$

(5) says that a measure makes labor less productive, as in Jones et al. (2020). For instance, production may require coordination and interaction among workers, and a measure such as social distancing or partial business opening makes it more difficult to coordinate and interact, reducing production efficiency (Koren and Petö 2020). With a measure, some tasks can be completed online but may not be done as efficiently as in a physical workplace. The loss of production efficiency, measured by $\phi(\theta)$, is assumed to increase in θ. Given the difference between two types of goods, the subsequent analysis assumes

$$\phi_a'(\theta) \geq \phi_b'(\theta) > 0. \tag{6}$$

Thus, a measure or an increase in its stringency affects production more in sector a.

The sector-i worker earns $w_i L_i(\theta)$ with w_i denoting the wage in sector i, and the budget constraint reads as

$$P_A A_i + P_B B_i = w_i L_i(\theta). \tag{7}$$

The model above is simple enough to generate closed-form solutions but has limitations. First, in (2), consumption of A is assumed to be the same as $A(\theta)$. In reality, the constraint may not be binding and $A < A(\theta)$ for some individuals. However, the model is restricted to identical individuals and assumes that the constraint is binding, because otherwise the severity θ plays no role.

Second, constraint (7) assumes that income is completely spent on A and B. In practice, individuals may save out of their income. However, the analysis is restricted to a one-period model, and saving is not considered.

Third, u_i in (1) assumes disutility of labor. More generally, workers value leisure, and u_i could be written as

[1] If $L_i = \ell_i(1 - \phi_i)$, as in an earlier version of this paper, it does not affect the analysis qualitatively, but makes the presentation of the basic idea more complicated.

$$u_i \equiv (A_i)^\alpha \ (B_i)^\beta + \Psi(z_i), z_i \equiv \overline{\ell} - \ell_i, \Psi' > 0, \Psi'' \leq 0,$$

where z_i denotes leisure and $\overline{\ell}$ is the maximum amount of time available for leisure or production. (1) essentially assumes a linear leisure function, so that $\Psi(z_i) = z_i = \overline{\ell} - \ell_i$ to obtain closed-form solutions.

2.3 Equilibrium

A sector-i worker chooses A_i, B_i and ℓ_i, subject to constraints (2) and (7), to maximize $u_i(\theta)$. As shown in the appendix,[2]

$$A_i = A(\theta) \ \ and \ \ B_i = [\frac{P_B}{\beta A(\theta)^\alpha w_i}]^{1/(\beta-1)}, i = a, b,$$

$$\ell_i = \frac{1}{w_i} A(\theta)[(\beta w_i)^{1/(1-\beta)} P_B^{\beta/(\beta-1)} + P_A] + \phi_i(\theta), i = a, b. \tag{8}$$

One unit of effective labor is assumed to produce one unit of the good in each sector. Since sector i employs n_i workers and each supplies $L_i(\theta)$ units of effective labor, the supply of a good equals $n_i L_i(\theta)$. In equilibrium,

$$n_a A_a + n_b A_b = (n_a + n_b) A(\theta) = n_a L_a(\theta),$$

$$n_a B_a + n_b B_b = n_b L_b(\theta). \tag{9}$$

In addition, in equilibrium,

$$w_a = P_A \ \text{ and } \ w_b = P_B. \tag{10}$$

Only the relative price can be determined, so

$$P_A = s^{(\beta-1)/\beta} \ \beta^{-1/\beta} P_B = s^{(\beta-1)/\beta} \ \beta^{-1/\beta}, \ s \equiv \frac{n_a}{n_b}, \tag{11}$$

where P_B is set at one.

Using (8) through (11),

$$A_a = A_b = A(\theta), \ B_a = A(\theta) \ (\beta P_A)^{1/(1-\beta)}, \ B_b = A(\theta) \ \beta^{1/(1-\beta)}. \tag{12}$$

3 Policy choice of a measure

Substituting (8) and (12) into (1), it can be shown again in the appendix that

$$v_a(\theta) = [\frac{(1-\beta)}{\beta s} - 1] A(\theta) - \phi_a(\theta) - h_a(\theta),$$

[2] All results below are derived in the appendix.

$$v_b(\theta) = [(1-\beta)\beta^{\beta/(1-\beta)} - s^{(\beta-1)/\beta}\ \beta^{-1/\beta}]A(\theta) - \phi_b(\theta) - h_b(\theta). \quad (13)$$

The first term of $v_a(\theta)$, $[\frac{(1-\beta)}{\beta s} - 1]A(\theta)$, shows the utility of consumption and disutility of supplying effective units of labor $L_a(\theta)$. That is, $(A(\theta))^\alpha (B_a)^\beta - L_a(\theta) = [\frac{(1-\beta)}{\beta s} - 1]A(\theta)$ once consumption and labor supply are chosen to maximize the utility. The sign of the expression inside the pair of square brackets, $\frac{(1-\beta)}{\beta s} - 1$, plays an important role and depends on the magnitude of $s = n_a/n_b$, the (relative) size of sector a in (11). Thus, an increase in the stringency of a measure, that limits $A(\theta)$ more, may increase or decrease the utility, depending on s. The second term of $v_a(\theta)$, namely $-\phi_a(\theta)$, represents the disutility of supplying non-productive labor. That is, to supply effective units of labor $L(\theta)$, a sector-a worker has to supply $\ell_a(\theta) = L_a(\theta) + \phi_a(\theta)$. $\phi_b(\theta)$ in $v_b(\theta)$ can be interpreted analogously.

Given the difference in the utilities in (13) between sector-a workers and sector-b workers, they prefer different policies. Letting θ_i maximize $v_i(\theta)$, θ_i satisfies the FOC (first-order condition) for an interior maximum of $v_i(\theta)$,

$$v'_a(\theta_a) = [\frac{(1-\beta)}{\beta s} - 1]A'(\theta) - \phi'_a(\theta) - h'_a(\theta) = 0, \quad (14)$$

$$v'_b(\theta_b) = [(1-\beta)\beta^{\beta/(1-\beta)} - s^{(\beta-1)/\beta}\ \beta^{-1/\beta}]A'(\theta) - \phi'_b(\theta) - h'_b(\theta) = 0. \quad (15)$$

The SOC (second-order condition) is assumed satisfied and $v''_i(\theta) < 0$, so that the comparative statics results below can be signed. Nevertheless, sufficient conditions for the satisfaction of the SOC are briefly discussed.

Since the benefit of an increase in the severity of the measure is the reduction in health risk $h_i(\theta)$ while the cost is the loss of production efficiency and consumption of A, it appears to be reasonable to assume $h''_i(\theta) \geq 0$, $\phi''_i(\theta) \geq 0$ and $A''(\theta) \leq 0$. That is, the cost, $\phi_i(\theta)$ or $-A(\theta)$, is increasing at an increasing rate,[3] and the benefit, $-h(\theta)$, is increasing at a decreasing rate. Since $v''_i(\theta)$ is identical to $v'_i(\theta)$, except that $A''(\theta), \phi''_i(\theta)$ and $h''_i(\theta)$ replace $A'(\theta), \phi'_i(\theta)$ and $h'_i(\theta)$, respectively, $v''_i(\theta)$ still cannot be signed with these assumptions, because the term involving $A''(\theta)$ can be positive or negative. To have a sense of sufficient conditions, consider an example: $A(\theta) = \lambda - \theta^\gamma, \gamma \in (1,2), \lambda$ being large and $A(\theta) > 0$ for a range of θ under consideration, $\phi_i(\theta) = i\theta^\delta, \delta > 2$ and $h_i(\theta) = i\theta^{-\epsilon}, \epsilon > 0, i = a, b, a > b > 0$. Letting $Q_i, i = a, b$, denote the expression inside the pair of square brackets in (14) and (15), $v''_a(\theta)$ and $v''_b(\theta)$ are, respectively,

$$v''_a(\theta) = -Q_a\gamma(\gamma-1)\theta^{\gamma-2} - a\delta(\delta-1)\theta^{\delta-2} - a\epsilon(\epsilon+1)\theta^{-\epsilon-2},$$
$$v''_b(\theta) = -Q_b\gamma(\gamma-1)\theta^{\gamma-2} - b\delta(\delta-1)\theta^{\delta-2} - b\epsilon(\epsilon+1)\theta^{-\epsilon-2}.$$

Given $\delta > 2$ and $\epsilon > 0$, the second term and the third term of $v''_a(\theta)$ are negative. Q_a in (14) cannot be signed in general. If $Q_a \geq 0$, the first term is also negative, given

[3] The loss of consumption of A is $A_i - A(\theta)$ but is written as $-A(\theta)$, as the effect of θ on the loss depends on $-A(\theta)$.

$\gamma \in (1,2)$, so $v_a''(\theta) < 0$. If $Q_a < 0$, the first term is positive and the sign of $v_a''(\theta)$ cannot be determined. A sufficient condition for $v_a''(\theta) < 0$ is $a > a^*$ with a^* denoting a critical value of a, because $v_a''(\theta)$ decreases in a. The same comment applies to $v_b''(\theta)$, and a sufficient condition for $v_b''(\theta) < 0$ is $b > b^*$.

The question concerns the relationship between s and the preferred choice θ_i. Given $v_i''(\theta) < 0$, the sign of $\partial\theta_i/\partial s$ is identical to that of

$$\frac{\partial \theta_a}{\partial s} \cong \frac{\partial v_a'(\theta_a)}{\partial s} = -\frac{(1-\beta)}{\beta}\frac{1}{s^2}A'(\theta) > 0, \tag{16}$$

$$\frac{\partial \theta_b}{\partial s} \cong \frac{\partial v_b'(\theta_b)}{\partial s} = \frac{(1-\beta)}{\beta} s^{-1/\beta}\, \beta^{-1/\beta} A'(\theta) < 0, \tag{17}$$

where '$\cong$' means 'the same sign as.' These results can be stated as:

Proposition 1 $\partial\theta_a/\partial s > 0$ *and* $\partial\theta_b/\partial s < 0$ *(as the number of sector-a workers increases relative to that of sector-b workers, sector-a workers prefer a more-stringent measure while sector-b workers prefer a less-stringent measure).*

The intuition of the result is simple. As in (14), the utility-maximizing θ_a balances the marginal benefit of an increase in the stringency, resulting from the reduction in the health risk $-h_a'(\theta)$, and the marginal cost from the reduction in the economic utility, the remaining terms in (14). An increase in the ratio $s = n_a/n_b$ increases the supply of labor in sector a, relative to sector b, decreasing the price of good A, P_A. Sector-b workers gain from a lower price P_A as they consume it. Sector-a workers lose from the lower price even though they also consume A, as their wages decrease.[4] Thus, if s is larger, the economic utility of a sector-a worker is lower, and so is the marginal cost of the increase in the stringency. Sector-a workers thus prefer to increase the stringency when s is larger, as in (16). The decrease in P_A, due to an increase in s, increases the economic utility of a sector-b worker and hence increases the marginal cost of the increase in the stringency. Sector-b workers thus prefer to reduce the stringency in response to an increase in s.

The proposition does not say that sector-b workers gain and sector-a workers lose from an increase in the severity. Rather, both lose (and enjoy the health gain), but sector-a workers lose less from an increase in the severity when s increases. The proposition does not say that sector-a workers prefer a more-stringent measure than sector-b workers, either. Rather, the proposition is about the response of a worker in each sector to an increase in s. A policy implication of the proposition is stated as:

Corollary 1 *Assume that* $n_b > n_a$, *and a majority of voters chooses the stringency of a measure or a policymaker chooses the stringency preferred by the majority. Then,* $\partial\theta_b/\partial s < 0$ (*if sector-b workers constitute a majority, the measure is less stringent in a jurisdiction with a larger number of sector-a workers relative to that of sector-b workers*).

With the assumption, the corollary follows from proposition 1. The question concerns which of two sectors constitutes a majority. The relationship between n_a

[4] That is, they are net suppliers of good A.

and n_b is an empirical issue. However, as noted in the Introduction, a measure appears to affect disproportionately a minority of workers. For instance, workers in the leisure and hospitality industry such as restaurants and hotels (Barrot et al. 2020; Suneson 2020) have been hit hardest during the Covid-19 pandemic, and those workers account for about 11% of the labor force in the U.S., as discussed in the next section (Bureau of Labor Statistics 2020). Other contact-intensive sectors may include the trade and transportation industry such as retail stores, and cruises and airlines. The sum of these sectors still constitutes a minority of the labor force. In fact, Koren and Petö (2020) find that about 49 million workers are in the contact-intensive sectors in the U.S., about 30% of the labor force. The assumption of $n_b \geq n_a$ thus appears to be reasonable. The corollary serves as the empirical hypothesis in Sect. 4, as the size of sector a and the stringency vary across states.

4 Empirical analysis

4.1 Data and variables

The dependent variable is **duration**, which equals the duration (the number of days) of a statewide stay-at-home order, compiled by Tolbert et al. (2020). A longer duration is interpreted as a more stringent measure. The hypothesis concerns the effects of the size of sector a on the stringency of a measure, **duration**, at the time of making policies (issuing the orders). That is, given information available at that time, the question is how the size of sector a affected the stringency of the measure. States had imposed statewide stay-at-home orders once between March 2020 and April 2020. California first issued the order on March 19, 2020. By April 6, 2020, 42 states and D.C. had issued the orders, but eight states did not issue.[5]

The key independent variable is the size of the contact-intensive sectors. Two sector-a variables are considered. **sector-a1** equals the percentage of employment in the leisure and hospitality industry such as hotels and restaurants. **sector-a2** equals the percentage of employment in the leisure and hospitality industry plus that in the trade and transportation industry such as retail stores, and cruises and airlines. These two industries have been greatly affected by the pandemic and are consistent with the notion of the contact-intensive industries in recent research findings (Barrot et al. 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, but the percentage of employment in **sector-a1** or **sector-a2** had been stable at least for the past five years. All data below is from the most recent available sources before the pandemic.

The regressions include other variables. First, there are three health variables. **old** equals the percentage of the population 65 years or older, and this variable is included as the old are known to be at risk. **vulnerability** measures the extent to which a state is vulnerable to the Covid-19 pandemic and is based on 20 factors

[5] Eight states are Arkansas, Iowa, Nebraska, North Dakota, Oklahoma, South Dakota, Utah, and Wyoming.

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. **deathrate** is the number of confirmed deaths resulting from Covid-19 per 100,000 population and is expected to affect the stringency. **deathrate** had evolved over time, and it is assumed that states used information as of the order-issuing dates, and states with no order did as of March 26, 2020, the average date among those states with the orders.[6]

Second, political ideologies often shape policies, especially pandemic-related policies. For instance, Democrats and Republicans differ in their beliefs about the health risks associated with the virus and behave differently (Allcott et al. 2020). To control for the difference, the governor's party affiliation and the partisan composition of the legislature of each state are considered. In particular, **partisan** equals 1 if a state is controlled by Democrats, and - 1 if controlled by Republicans, and zero if divided. In addition, to see if measures in swing states differ from others, **swing** is added, a dummy variable equal to 1 if a state is a swing state, and 0 otherwise.

Third, there are other controls. **density** equals the number of residents per square mile, and the pandemic is expected to affect denser areas more adversely. **percapitagdp** equals per capita gross state product and may be viewed as a broad control. These seven variables come from Index Mundi (2020), Barclay and Rodriguez (2020), University of Oxford (2020), the National Conference of State Legislatures (2020), Gilbert (2020), State Key Data (2020) and U.S. Bureau of Economic Analysis (2020), respectively.

Table 1 presents summary statistics. **duration** ranges from 0 day in the eight states with no order to 90 days. In California, Kentucky, Maryland, New Jersey, Oregon and West Virginia, the duration is indefinite ('until revoked') at the time of issuing the orders and is assumed to be 90 days,[7] as the longest duration among the states with a definite time line is 72 days. If it is set at 80 days or 100 days, it changes the regression results little. **sector-a1** and **sector-a2** are on average 11.2% and 29.4%, respectively. About 30% of jobs in the U.S. 'rely heavily on face-to-face communication or require close physical proximity to other workers' (Koren and Petö, 2020), so **sector-a2** is close to their estimates and considered a broader notion of the contact-intensive industries. **old**, **vulnerability**, **deathrate**, **density** and **percapitagdp** are on average 16.4%, 45, 0.3, 424, and $59,267, respectively. As for **partisan**, 15 and 22 states are controlled by Democrats and Republicans, respectively, and 13 states are divided. There are six swing states, Arizona, Florida, Michigan, North Carolina, Pennsylvania and Wisconsin, so the mean of **swing** equals 0.12. **sector-a1iv** and **sector-a2iv** serve as instruments for **sector-a1** and **sector-a2** for IV estimation results and will be discussed more. Data on **vulnerability**, **partisan** and **percapitagdp** is not available for D.C., so there are 50 observations for the three variables.

[6] Different assumptions regarding the time of **deathrate** have no qualitative effect on the results. For instance, if those states with no order are assumed to use information as of March 20 or March 31 or April 5, it affects little the results.

[7] The analysis again concerns how the stringency of a measure was determined at the time of making policies (the time of issuing the orders).

Table 1 Summary statistics

Variables	# of observations	Mean	Standard deviation	Minimum	Maximum
Duration	51	42.29412	27.22888	0	90
Sector-a1	51	.1120443	.025549	.0925188	.2484751
Sector-a2	51	.2943509	.0357571	.144421	.4297833
Vulnerability	50	45.02	10.90469	17.2	74.1
Old	51	16.40392	1.962647	11.1	20.6
Deathrate	51	.3097929	.4053291	0	1.550737
Partisan	50	−.14	.8573809	−1	1
Swing	51	.1176471	.3253957	0	1
Density	51	423.6731	1603.909	1.288269	11500.77
Percapitagdp	50	59266.96	11342.82	38721.62	87518.41
Sector-a1iv	51	.1102516	.0270869	.089693	.2634207
Sector-a2iv	51	.2968759	.0370573	.1398871	.4498695

4.2 Regression results

Table 2 shows regression results with **duration** as the dependent variable and **sector-a1** as the size of the contact-intensive sector. It appears that a health variable and the political variable, **partisan**, along with a **sector-a** variable, play an important role in explaining **duration**. Thus, specifications (i) through (iii) include one of the three health variables, with **sector-a1** and **partisan** in all three specifications. Specification (iv) includes all variables.

The coefficients of **sector-a1** are negative in all specifications. To relate this result to the model, note that sector-*a* workers prefer to increase the duration of the stay-at-home order in (16) and sector-*b* workers prefer to decrease it in (17), as the size of the contact-intensive sectors increases. Thus, the negative coefficients of **sector-a1** are consistent with (17), but not with (16). However, under the maintained assumption in corollary 1, sector-*b* workers constitute a majority, and the policymaker of a jurisdiction determines the stringency to maximize the utility of sector-*b* workers. As a result, the model predicts (17), and the negative coefficients of **sector-a1** are consistent with model predictions in corollary 1.

The significance of the coefficient of **sector-a1** depends on the health variable included. The coefficient of **sector-a1** is significant at the 1% level with **vulnerability** in (i), but it is significant at the 5% level with **old** in (ii) or **deathrate** in (iii). It is significant at the 5% level with all variables in (iv). The coefficient of **sector-a1** ranges from -267 in (iii) to -346 in (i), so a one-percentage point increase in the size of the intensive sector decreases the duration by 2.67 days in (iii) and by 3.46 days in (i), given that **sector-a1** is expressed as a decimal number such as 0.23 rather than 23%. To have a sense of the explanatory power of **sector-a1**, note that the standard deviation of **sector-a1** is 0.0255, and that of **duration** is 27.23 in Table 1. Thus, in (iii), a one-standard-deviation increase in **sector-a1** decreases **duration** by 267 x 0.0255 = 6.81, explaining about 25% (=

Table 2 Regression results with **sector-a1**

	(i)	(ii)	(iii)	(iv)
Sector-a1	−345.792***	−274.9733**	−266.8027**	−330.7654**
	(119.8558)	(136.56)	(127.5699)	(132.7119)
Vulnerability	.7653046**			.717882*
	(.3735397)			(.3928286)
Old		1.765534		−.7456458
		(1.79144)		(1.705172)
Deathrate			.9920376	−.03725
			(6.296802)	(6.919896)
Partisan	22.65822***	19.19235***	19.74105***	22.30417***
	(3.079977)	(3.741506)	(3.643507)	(4.206323)
Swing				4.428498
				(8.160822)
Density				.0176861
				(.0159299)
Percapitagdp				−.0002864
				(.0003663)
Constant	49.77248***	46.67837	74.6637***	75.34485
	(16.58861)	(32.28195)	(14.05992)	(47.25177)
N	50	50	50	50
F	19.98	16.40	13.89	8.79
Prob > *F*	0.0000	0.0000	0.0000	0.0000
R-squared	0.4514	0.3847	0.3707	0.4771

[1]The numbers in parentheses in all regressions are robust errors

[2]***, ** and * indicate statistical significance at the 1%, 5% and 10%, respectively

6.81/27.23) of the standard deviation of **duration**. Likewise, in (i), a one-standard-deviation increase in **sector-a1** explains about 32.4% (= 346 x 0.0255/27.23) of the standard deviation of **duration**.

As for health variables, the coefficients of **vulnerability**, **old** and **deathrate** are positive, as expected, although the coefficients of **old** and **deathrate** become negative in (iv). The coefficient of **vulnerability** in (i) is significant at the 5% level, but that of **old** in (ii) or **deathrate** in (iii) is not significant.[8] When all variables are included in (iv), the coefficient of **vulnerability** becomes significant at the 10% level.

The positive coefficients of **partisan** in all specifications show that the duration tends to be longer in Democrat-controlled states. This result is consistent with findings in the literature that Democrats are more likely to adhere to mitigation

8 The reason for the insignificant coefficient of **deathrate** may be that it was relatively low at the time of issuing orders (the median of **deathrate** is 0.13 per 100,000 population).

measures and place more emphasis on health risks than Republicans (Allcott et al. 2020; Beauchamp 2020; Coppins 2020). The coefficients of **partisan** are significant at the 1% level in all specifications. The coefficient of **swing** is positive, but not significant, so swing states do not appear to differ from others.

Regarding other controls, the coefficient of **density** is positive, as expected. The coefficient of **percapitagdp** is negative. There is no expected sign of the coefficient of **percapitagdp**, but the negative sign may mean that a larger economy may lose more from an order and may shorten the duration. Neither coefficient is significant.

duration was set to 0 for 8 states with no order and set to 90 for 6 states with no definite time line. Tobit regressions were considered, as 0 and 90 can be viewed as corner solutions to the determination of an optimal duration that balances the health benefits and the economic losses. Although the results are not reported to conserve space, the results remain little affected.

Table 3 is identical to Table 2, except that **sector-a2** replaces **sector-a1**. The results in Table 3 are qualitatively the same as those in Table 2 in the sense that the signs of all coefficients in Table 3 coincide with those in Table 2. The

Table 3 Regression results with **sector-a2**

	(i)	(ii)	(iii)	(iv)
Sector-a2	−279.5858**	−202.5245*	−198.8784*	−263.6453**
	(110.1653)	(111.9564)	(111.03)	(119.9383)
Vulnerability	.7773274**			.7488907*
	(.3641687)			(.3965666)
Old		1.602803		−.9789379
		(1.767917)		(1.72923)
Deathrate			.4703691	−.516896
			(6.296802)	(7.078064)
Partisan	20.1836***	17.26143***	17.80367***	20.01209***
	(3.327375)	(4.060211)	(3.885856)	(4.170779)
Swing				4.51641
				(7.942564)
Density				.017624
				(.0170958)
Percapitagdp				−.0002747
				(.000409)
Constant	93.20512***	78.44695*	103.7323***	118.1883*
	(28.48506)	(43.69933)	(32.22827)	(62.8295)
N	50	50	50	50
F	15.75	14.83	13.50	6.63
Prob $> F$	0.0000	0.0000	0.0000	0.0000
R-squared	0.4374	0.3673	0.3556	0.4628

coefficients of **sector-a2** are less significant than those of **sector-a1**. In particular, it is significant at the 10% level in (ii) and (iii), but at the 5% level in (i) and (iv). The coefficients of **sector-a2** range from -199 in (iii) to -280 in (i). The coefficients mean that a one-percentage point increase in the size of the intensive sector, measured by **sector-a2**, decreases the duration by 1.99 days in (iii) and by 2.8 days in (i). To see the explanatory power of **sector-a2**, note that the standard deviation of **sector-a2** is 0.0358, so a one-standard-deviation increase in **sector-a2** decreases **duration** by 199 x 0.0358 = 7.12, explaining about 26.1% (= 7.12/27.23) of the standard deviation of **duration** in (iii). Likewise, in (i), a one-standard-deviation increase in **sector-a2** explains about 36.8% (= 280 x 0.0358/27.23) of the standard deviation of **duration**. The explanatory power of **sector-a2** is thus about the same as that of **sector-a1** in Table 2.

To take into account the possibility of omitted variables bias, instrumental variables for sector-*a* variables are considered, and IV estimation results are presented in Table 4. The average of the past five years of percentage of employment is used as an instrument.[9] That is, **sector-a1iv** equals the five-year average of **sector-a1** for 2015 through 2019, and similarly for **sector-a2iv**. First-stage weak instrument statistics, the Cragg-Donald Wald F Stat and the Kleibergen-Paap Wald F stat, in the table show that **sector-a1iv** or **sector-a2iv** does not appear to be a weak instrument.

Table 4 includes regression results with both **sector-a1** and **sector-a2**. (i) and (ii) use **sector-a1**, and (iii) and (iv) use **sector-a2**. Rather than each of the three health variables, only one health variable, **vulnerability**, is considered in (i) and (iii) again in order to conserve space. (ii) and (iv) include all variables. Comparing Tables 2 and 3 with Table 4, IV estimation results are qualitatively the same as those in Tables 2 and 3 in the sense that the signs and explanatory power of the key variables, **sector-a1** and **sector-a2**, remain largely unaffected. The coefficients of the two variables are significant at the 1% level in all specifications. Although not reported, with **old** or **deathrate** replacing **vulnerability** in (i) and (iii), the coefficients of **sector-a1** and **sector-a2** become significant at the 5% level.

The coefficients of other variables change little. In particular, the coefficients of **vulnerability** are positive and significant at the 5% level, as in Tables 2 and 3. **partisan** continues to have a positive significant effect on **duration**. The coefficient of **density** is again positive while that of **percapitagdp** is negative, but they are not significant.

5 Conclusion

The paper has studied the heterogeneous welfare effects of measures intended to mitigate health risk during a pandemic. The analysis has shown that the size of the contact-intensive sector plays an important role in the stringency of a measure and hence in political support for the measure. Available empirical evidence confirms

[9] With the 10-year average, the results change little.

Table 4 IV estimation results with **sector-a1** and **sector-a2**

	(i)	(ii)	(iii)	(iv)
Sector-a1	−346.508***	−330.4217***		
	(110.6311)	(115.7152)		
sector-a2			−299.1845***	−278.3177***
			(100.2128)	(102.1833)
Vulnerability	.7657357**	.7177295**	.792765**	.7587847**
	(.3585762)	(.3557481)	(.3465168)	(.3575151)
Old		−.7454604		−1.001854
		(1.54288)		(1.551654)
Deathrate		-.0399103		−.4011
		(6.214822)		(6.338086)
Partisan	22.6644***	22.29994***	20.2192***	20.1112***
	(2.973823)	(3.815242)	(3.219954)	(3.81238)
Swing		4.42887		4.501341
		(7.391462)		(7.20224)
Density		.017691		.0173596
		(.0144248)		(.0155238)
Percapitagdp		−.0002863		−.000281
		(.0003316)		(.0003718)
Constant	49.83431***	75.30146*	98.34278***	122.8963**
	(15.605)	(42.4655)	(25.99274)	(55.16374)
N	50	50	50	50
F	19.84	8.80	15.38	6.61
Prob > *F*	0.0000	0.0000	0.0000	0.0000
R-squared	0.4514	0.4771	0.4370	0.4626
Cragg-Donald Wald F statistic	3329.983	3119.916	1703.131	1559.055
Kleibergen-Paap Wald F statistic	568.501	552.094	379.042	305.851
Stock-Yogo critical values (10%)	16.38	16.38	16.38	16.38
Stock-Yogo critical values (15%)	8.96	8.96	8.96	8.96

the analysis and shows that the duration of stay-at-home orders tends to be shorter in states with a larger contact-intensive sector.

The analysis highlights the importance of multisectors in studying the economic effects of measures. In particular, the size of the contact-intensive sectors shapes the stringency of measures, not because they constitute a majority, but because the majority or the non-contact-intensive sectors benefit from a larger share of the contact-intensive sectors. This benefit effect occurs as production in a sector is related to another through consumption and illustrates the value of a multisector model. The role of the interaction between sectors in the determination of mitigation measures has received little attention but appears to deserve more research.

Appendix

Proof of (8) A sector-i worker chooses $(A_i, B_i, \ell_i, \eta_{i1}, \eta_{i2})$ to maximize

$$M_i \equiv (A_i)^{\alpha}(B_i)^{\beta} - \ell_i + \eta_{i1}[A(\theta) - A_i] + \eta_{i2}[w_i(\ell_i - \phi_i(\theta)) - P_A A_i - P_B B_i],$$

where η_{i1} and η_{i2} are the multipliers. The FOCs for an interior maximum of M_i are

$$\begin{aligned}
\frac{\partial M_i}{\partial A_i} &= \alpha(A_i)^{\alpha-1}(B_i)^{\beta} - \eta_{i1} - \eta_{i2}P_A = 0,\\
\frac{\partial M_i}{\partial B_i} &= \beta(A_i)^{\alpha}(B_i)^{\beta-1} - \eta_{i2}P_B = 0,\\
\frac{\partial M_i}{\partial \ell_i} &= -1 + \eta_{i2}w_i = 0,\\
\frac{\partial M_i}{\partial \eta_{i1}} &= A(\theta) - A_i = 0,\\
\frac{\partial M_i}{\partial \eta_{i2}} &= w_i(\ell_i - \phi_i(\theta)) - P_A A_i - P_B B_i = 0.
\end{aligned}$$

$\partial M_i/\partial \eta_{i1} = 0$ leads to $A_i = A(\theta)$. Substitution of $\eta_{i2} = 1/w_i$ from $\partial M_i/\partial \ell_i = 0$ into $\partial M_i/\partial B_i = 0$ gives the expression of B_i in (8). Substituting $A_i = A(\theta)$ and the expression of B_i into $\partial M_i/\partial \eta_{i2} = 0$ and solving the resulting equation for ℓ_i, the expression of ℓ_i in (8) is obtained. □

Proof of (11) Only one equilibrium condition matters, given two goods. The first one in (9) leads to

$$(n_a + n_b)A = n_a L_a = n_a(\ell_a - \phi_a) = n_a A\left[(\beta P_A^{\beta})^{1/(1-\beta)} + 1\right] \implies n_b = n_a(\beta P_A^{\beta})^{1/(1-\beta)},$$

where $A = A(\theta)$, and the expression of ℓ_a in (8) is used. The condition can be solved for P_A, and the solution is in (11). □

Proof of (12) Substitution of the expression of P_A in (11) and that of ℓ_i in (8) into the expression of B_i in (8) leads to (12). □

Proof of (13) Using the expression of B_a in (12) and that of ℓ_a in (8),

$$\begin{aligned} u_a &= A^{\alpha}\left[A(\beta P_A)^{1/(1-\beta)}\right]^{\beta} - \ell_a \\ &= A(\beta P_A)^{\beta/(1-\beta)} - \left[A(\beta P_A^{\beta})^{1/(1-\beta)} + A + \phi_a\right] \\ &= A\left[(\beta P_A)^{\beta/(1-\beta)} - (\beta P_A^{\beta})^{1/(1-\beta)} - 1\right] - \phi_a. \end{aligned}$$

Substitution of P_A in (11) into the last expression above and subtraction of $h_a(\theta)$ give $v_a(\theta)$ in (13). The expression of $v_b(\theta)$ can be obtained in an analogous manner. □

Consumption health risk

The utility function in (1) is modified as

$$v_i(\theta) = (A_i)^{\alpha}(B_i)^{\beta} - \mu(\theta)A_i - \ell_i - h_i(\theta).$$

$\mu(\theta)$ represents the risk involved in consumption of A. A measure is assumed to reduce the risk, so $\mu'(\theta) < 0$.

The utilities in (13) are modified as

$$v_a(\theta) = \left[\frac{(1-\beta)}{\beta s} - 1 - \mu\right]A - \phi_a - h_a,$$

$$v_b(\theta) = \left[(1-\beta)\beta^{\beta/(1-\beta)} - s^{(\beta-1)/\beta}\,\beta^{-1/\beta} - \mu\right]A - \phi_b - h_b. \tag{18}$$

The FOCs in (14) and (15) become

$$v_a'(\theta_a) = \left[\frac{(1-\beta)}{\beta s} - 1\right]A' - (\mu A)' - \phi_a' - h_a' = 0, \tag{19}$$

$$\begin{aligned} v_b'(\theta_b) = \left[(1-\beta)\beta^{\beta/(1-\beta)} - s^{(\beta-1)/\beta}\,\beta^{-1/\beta}\right]A' \\ -(\mu A)' - \phi_b' - h_b' = 0. \end{aligned} \tag{20}$$

Although (19) and (20) include the additional term $-(\mu A)'$, relative to (14) and (15), it does not affect the key result in proposition 1 and corollary 1, namely the sign of $\partial\theta_a/\partial s$ and $\partial\theta_b/\partial s$.

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