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Optimizing Social Assistance Strategies in Response to the COVID-19 Crisis

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ABSTRACT

The COVID-19 pandemic highlighted significant challenges in designing social assistance strategies for crisis management. This study investigates optimal approaches using theoretical modeling and multinomial logit analysis of data from 47 countries during the pre-vaccination phase of 2020. The findings underscore the importance of combining conditional (targeted) and unconditional (universal) social assistance measures, with unconditional assistance prioritized in severe crises due to its rapid implementation and broad reach. By addressing the complexities of resource allocation and policy implementation under crisis conditions, this study provides actionable insights for public policy design, emphasizing the need for robust budgetary systems to sustain multifaceted strategies, mitigate immediate impacts, and build resilience against future disruptions.

Keywords*:* COVID-19, disaster mitigation, social assistance strategies, conditional vs. unconditional support.

JEL classifications: C54, H12, H53, I31.

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1. Introduction

The COVID-19 pandemic presented unprecedented social, economic, and political challenges globally, exacerbating pre-existing socioeconomic inequalities and significantly shaping the crisis' impact (Botha et al., 2021; Clouston et al., 2021). The pandemic placed intense financial strain on households, especially in low- and middle-income countries, where sudden job losses, business closures, and disruptions in informal employment drove many deeper into poverty. This threatened the livelihoods of millions worldwide, similar to the broader impacts observed during previous health emergencies (McIntyre et al., 2006; Forman et al., 2022; Khan et al., 2024). In response, countries implemented diverse social assistance measures, prioritizing conditional (targeted) support aimed at protecting individuals directly affected by the pandemic. Conditional social assistance policies, designed to allocate resources efficiently through criteria such as income or employment status, were initially favored by many governments, to deliver aid precisely to those most in need. In practice, these strategies faced significant obstacles, where accurately identifying vulnerable individuals and delivering timely assistance proved difficult, as delays and administrative bottlenecks became major barriers during severe crises (Asenjo et al., 2024).

These challenges created opportunities for unconditional (universal) policies, which, due to their inclusive nature and faster implementation, emerged as a critical alternative during the crisis. Unlike conditional assistance, which is often burdened by eligibility assessments and distribution delays, unconditional assistance can be quickly deployed to a broad segment of the population, providing immediate relief and ensuring coverage across diverse demographics (Gentilini et al., 2022; Banerjee et al., 2017; Bastagli et al., 2016). This shift raises a central question: Given different levels of crisis severity, which form of social assistance—conditional or unconditional—is optimal in addressing the needs of the population?

As countries implemented stringent public health measures—ranging from lockdowns to social distancing measures—social assistance programs emerged as essential tools for supporting vulnerable populations, stabilizing economies, and maintaining social cohesion. These measures highlighted the critical need for governments to design and implement effective social policies capable of rapidly address the evolving crisis (Farzanegan and Gholipour, 2023; Tan et al., 2023; Parekh and Bandiera, 2020). However, discovering the optimal design of social assistance strategies for varying crisis conditions became crucial to providing the necessary support.

The welfarist approach traditionally emphasizes targeting social assistance for efficient resource allocation (Grosh et al., 2022a; Grosh et al., 2022b; Maleva et al., 2017). However, studies have increasingly questioned the effectiveness of targeted strategies, highlighting instances where such approaches have failed, particularly in contexts of significant economic and social crises (Bradbury, 2004). The COVID-19 pandemic further exposed the limitations of conditional social assistance, as many countries struggled to rapidly deliver aid to those most in need. This debate on whether social assistance measures should be targeted or universal points to the need for careful consideration of how these programs are designed and implemented to ensure both effectiveness and equity during crises.[2]

The COVID-19 pandemic can be categorized as a natural disaster, as pandemics carry risks shaped by social determinants such as vulnerability and exposure, which exacerbate existing inequalities and systemic disadvantages (Mussio et al., 2023; Seddighi, 2020; O'Flynn, 2020). This classification highlights the critical need for government interventions in relief and recovery. Such measures may include specialized disaster training programs for low-income households (Farzanegan et al., 2024) and addressing factors like the negative association between government trust and excess mortality during the pandemic (Farzanegan and Hofmann, 2022). Inclusive social assistance measures, as demonstrated during the COVID-19 crisis, also played a vital role in enhancing disposable incomes for lower-income groups. Beyond immediate relief, these measures fostered public trust in governmental institutions, mitigating the broader socioeconomic impacts of the crisis (O'Donoghue et al., 2023).

The severity of a natural disaster's impact often depends on the level of government preparedness and the effectiveness of its response (Cohen and Werker, 2008). While both preventive and palliative measures play critical roles in disaster response, a 'crisis of preparedness' was likely to occur due to the lack of information regarding the COVID-19 phenomenon (Chilton et al., 2020). With no established medical treatments or vaccines available before the pandemic, preventive measures shifted focus toward budget preparedness. Therefore, in this study, we set aside preventive measures and instead focus on two 'palliative' policy instruments available to governments: unconditional assistance, which provides universal support, and conditional assistance, designed to support those directly affected by COVID-19.

[2] Pestieau and Ponthiere (2022) highlight a similar dilemma in lockdown policies, where a utilitarian focus on maximizing welfare could save more lives but worsen economic inequalities, underscoring the ethical trade-offs in crisis policy design.

Our theoretical framework argues that conditional assistance is most effective during moderate crises, where resources can be allocated precisely. However, as the crisis intensifies, the need for rapid and widespread support becomes paramount, making unconditional assistance a more practical policy response. Unconditional assistance, free from the delays associated with eligibility assessments, ensures that aid reaches a broader segment of the population more quickly. In contrast, conditional assistance, though targeted, may not provide the necessary speed or coverage needed in severe crises. Our central argument is that in extreme situations, policymakers should prioritize universal social assistance over precise targeting, ensuring that budgetary systems are prepared to sustain such measures. Drawing on disaster mitigation theory, this study explores the optimal design and implementation of social assistance strategies to address the complex challenges posed by the COVID-19 pandemic through both theoretical modeling and empirical analysis.

The remainder of this paper is structured as follows: Section 2 reviews the countries' social assistance during COVID-19. Section 3 presents the theoretical framework. Section 4 outlines our cross-country empirical analysis. Finally, Section 5 draws policy implications and concludes the paper.

2. Social Assistance Case Studies

The extensive health and economic crises during the emergence of COVID-19 underscored the need for robust social assistance programs as pivotal components of the pandemic policy response. Social assistance programs that provided direct financial support to affected individuals and households played a significant role in addressing the immediate needs of the most vulnerable populations, while also stabilizing the broader economic landscape. Countries worldwide have implemented varied social assistance measures, ranging from unconditional cash transfers to more targeted interventions aimed at alleviating hunger, reducing poverty, and lessening social inequality. There is substantial evidence that measures like unconditional cash transfers have provided critical emergency relief to many households (Gerard et al., 2020). In the pre-vaccination phase, governments frequently used direct cash payments as a policy tool to offset income losses, including programs such as the Coronavirus Aid, Relief, and Economic Security (CARES) Act in the USA, the Canada Emergency Response Benefit (CERB), Korea's Emergency Relief Payment, Japan's emergency economic measure package, and Australia's Coronavirus Supplement (Gentilini et al., 2022).

Income support programs have proven essential for economically disadvantaged individuals who may feel compelled to continue working despite financial pressures (Aminjonov et al., 2023; Aubert and Augeraud-Véron, 2021; Hsiang et al., 2020). Targeting these disadvantaged individuals is a fundamental part of these programs, aiding in adherence to public health guidelines and producing beneficial health outcomes, while mitigating the socioeconomic impacts of the pandemic. Therefore, it is imperative to explore which forms of social assistance—conditional or unconditional—are most effective in providing relief and supporting public health objectives during such crises.

Drawing from global experiences, the real-world implementation and impacts of income support programs during the pandemic have varied, providing valuable insights into the effectiveness of different social assistance strategies. For example, Aminjonov et al. (2023) highlight that while lockdowns were less effective in reducing mobility among poorer regions in Africa, Latin America, and Asia, emergency income supports helped mitigate these disparities by providing financial stability to households, thus enabling them to comply with mobility restrictions. Similarly, in Latin America, extreme poverty often forced individuals to increase mobility in search of income, undermining isolation measures and exposing them to greater contagion risks, further underscoring the critical role of income support in addressing such vulnerabilities (Ratto et al., 2021). Additionally, Bui et al. (2022) report that pandemic-related financial support from the governments of Thailand and Vietnam not only improved consumer sentiment but also led to increases in both actual and planned durable spending. These measures contributed to a more optimistic macroeconomic outlook, enhanced trust in government, and improved personal well-being, demonstrating the multifaceted benefits of timely and well-targeted financial assistance.

Gerard et al. (2020) advocate for a comprehensive approach that combines government and community efforts, to effectively support the most vulnerable populations and mitigate the socioeconomic impacts of COVID-19, especially in developing countries. Their findings suggest that collaborative strategies can amplify the benefits of social assistance programs, enhancing their overall impact. In the United Kingdom, Brewer and Gardiner (2020) analyze how COVID-19 has impacted households, especially those with low incomes, revealing that measures like the Job Retention Scheme and enhanced Universal Credit have partially mitigated financial impacts but were insufficient in fully protecting living standards. The increased debt and decreased savings among poorer families underscore the need for more robust support mechanisms.

Asfaw (2021) provides evidence that income support programs significantly reduced COVID-19 case and mortality growth rates during the pandemic, illustrating the direct public health benefits of financial assistance. This supports the assertion that economic measures can also serve important public health functions by enabling adherence to social distancing guidelines. Koebel et al. (2021) examine the impact of COVID-19 in Canada and note that policies such as the Canada Emergency Response Benefit (CERB) and Canada Emergency Wage Subsidy (CEWS) were extensive but failed to adequately balance efficiency, equity, and worker voice, leading to suboptimal outcomes. They suggest that integrating universal and targeted basic income strategies could better meet public health goals and support economic resilience.

The case of Peru, as reported by Curi-Quinto et al. (2021), shows that 24% of the population experienced food insecurity during the initial phase of the pandemic. This was exacerbated by factors such as lower household wealth and larger family sizes. The ineffectiveness of government financial support, due to delays and poor targeting, highlights critical areas for improvement in policy design and implementation. In contrast, Lu et al. (2020) demonstrate how targeted social insurance, unemployment benefits, and healthcare initiatives in China effectively mitigated the impact of the COVID-19 crisis, supported vulnerable populations, and stabilized the economy. Similarly, Ashraf (2020) discusses how income support policies not only boost stock market returns, by increasing investor confidence, but also reduce infection rates, particularly among lower-income groups who are more likely to comply with social distancing if they receive financial support.

Amri and Drummond (2021) highlight how pre-existing issues, such as inadequate healthcare coordination and insufficient income supports, exacerbated the impact of COVID-19, prompting rapid policy shifts towards the implementation of income support measures to mitigate effects on vulnerable populations. Finally, O’Donoghue et al. (2020) analyze the distributional impacts of COVID-19 in Ireland, showing that both universal and targeted income support policies are crucial in mitigating the pandemic's harsher economic effects on lower-income groups. The study emphasizes the importance of precise targeting and timely application of these policies to effectively support the most vulnerable households during the crisis.

These diverse experiences highlight the complex challenges of designing effective social assistance during a global health crisis, emphasizing the need for adaptable, evidence-based policy frameworks. Building on these insights, this study explores the trade-offs between conditional (targeted) and unconditional (universal) policies in shaping effective responses. By analyzing how varying crisis severities influence the choice between these strategies, our research provides insights into their impact on social welfare, economic resilience, and public health outcomes. This examination helps clarify when conditional approaches may be more effective and when broad, unconditional measures are necessary to meet the demands of a severe crisis.

3. Theoretical Framework

3.1. Model Setup

To determine the optimal social assistance strategies during the COVID-19 crisis, we develop a formal disaster mitigation model grounded in economic theory and public policy analysis. We assume that the COVID-19 shock causes a monetized damage $k^i \geq 0$ to any individual i. The model incorporates the key variable $K = \sum k^i$, representing crisis severity, to assess the relative merits of different policy approaches according to government capacity and societal values. The overall social protection spending for each individual is $s^i + ak^i$, where s^i represents unconditional social assistance and ak^i signifies conditional social assistance as a fraction, a, of the damage.[3] Building on previous research in the political economy of natural disasters (Cohen and Werker, 2008), our model extends this analysis to the specific context of the COVID-19 pandemic, accounting for its unique challenges and dynamics.

We define a modified and monetized relief function as $f(s^i, ak^i)$. This relief function exhibits diminishing marginal returns: $f_1 > 0, f_2 > 0, f_{11} < 0, f_{22} < 0$. Here, f_{lk} represents the second derivative, with respect to the l-th and k-th elements of the function, while f_l represents the first derivative, with respect to the l-th element. Let $u^i(y^i)$ denotes the utility of an individual with exogenous income y^i. Consequently, the utility of a survivor affected by COVID-19 can be expressed as:

$$u^i\left(y^i + f\left(s^i, ak^i\right) - k^i\right). \tag{1}$$

[3] It is worth noting that, counterintuitively, the optimal level of *s* is not zero. This phenomenon is largely attributed to the fact that *s* can influence the probability of death by slowing down the spread of the virus.

Up to this point, we have focused on living individuals. Studies suggest that low-income households are more susceptible to fatalities resulting from COVID-19 infections, due to factors such as a lack of capacity to self-isolate and limited access to quality healthcare (Dashti et al., 2021; Decoster et al., 2021; Li et al., 2021; Papageorge et al., 2021; Drefahl et al., 2020; Hammitt, 2020). Alvarez et al. (2020) demonstrate that a high fatality rate of COVID-19 reinforces the motivation to implement lockdown restrictions. Therefore, it is imperative for governments to provide relief to numerous households during lockdowns (Perugini and Vladisavljević, 2021). Consequently, it is reasonable to assume that the probability of death resulting from the crisis is related to social assistance policies. The probability of death, denoted as $q^i = q\big(f(s^i, ak^i), y^i - k^i\big)$, exhibits the following properties: $q_1^i < 0, q_2^i < 0, q_{11}^i > 0, q_{22}^i > 0$. In other words, this probability decreases with increasing relief and income. From a government's point of view, given the value of each person's life, D^i, if a subset D of individuals lose their lives due to the crisis, then the societal loss is calculated as the sum of the values of those individuals, denoted as $\sum_{i \in D} D^i$.

3.2. Optimal Policy Design

The social welfare function is defined as:

$$W = \sum_1^n \delta^i \big[(1 - q^i) u^i\big(y^i + f(s^i, ak^i) - k^i\big) - q^i D^i\big] \tag{2}$$

where δ^i is the government's inherent interest in individual i. The government solves the following maximization problem:

$$Max_{a,s^i}\, W \tag{3}$$

$$s.t. \quad I - \gamma K = G + aK + \sum_1^n s^i$$

where I is the government's income, and γ $(0 < \gamma < 1)$ is a fraction of the total damage, K. Therefore, γK is the amount of income loss due to the COVID-19 crisis. G is the general government spending and $aK + \sum_1^n s^i$ is the cost of social assistance spending.[4] In Appendix

[4] The COVID-19 crisis significantly reduced tax revenues in two-thirds of OECD countries, due to the economic downturn and support measures provided through the tax system, leading to substantial fiscal pressures (OECD, 2021). Consequently, governments had limited capacity to use tax policy as a tool, prompting us to exclude it

A and B, first order and necessary conditions are outlined. We assume a specific form for the relief function:

$$f\left(s^i, ak^i\right) = f_s ln\left(s^i\right) + f_{ak} ln\left(ak^i\right) \tag{4}$$

With this functional form, the necessary conditions for the existence of an inner solution are satisfied. However, while this functional form is useful for exploring efficiency and optimal policy, it is not a vital presumption for our propositions.

Proposition 1: *If the government assigns a high value to individuals' lives, the optimal size of unconditional assistance for each person increases with the magnitude of the crisis, the value of life, and the government's inherent interest in social welfare. Meanwhile, it decreases with the individual's income.* In technical terms:

$$\frac{\partial s^{i^*}}{\partial K} > 0,\ \frac{\partial s^{i^*}}{\partial D^i} > 0,\ \frac{\partial s^{i^*}}{\partial \delta^i} > 0,\ \frac{\partial s^{i^*}}{\partial y^i} < 0. \tag{5}$$

Proofs are provided in Appendix C.

We now turn to the role of efficiency in selecting the optimal policy. To proceed, we utilize the previously specified functional form for the relief mechanism, as defined in equation (4)

Lemma 1: *Greater efficiency in implementing a policy increases the likelihood that the government will adopt the policy more extensively.* Technically:

$$\frac{\sum_{kj\neq 0} s^{j^*}}{a^* K} = \frac{f_s}{f_{ak}}. \tag{6}$$

This Lemma implies that the government should prioritize the policy it can implement most efficiently. If the government is effective in identifying individuals affected by the COVID-19 crisis, it should favor conditional social assistance. Otherwise, unconditional social assistance should be employed more frequently.

from our model and focus on direct spending measures instead. This approach aligns with the work of Cohen and Werker (2008).

In the next step, we compare the two policies irrespective of their effectiveness and conclude that a balanced use of both conditional and unconditional assistance is optimal.

Proposition 2: *If the government assigns a high value to individuals' lives, both conditional and unconditional assistance policies should be implemented for their population impact. Additionally, as the magnitude of the crisis increases, unconditional assistance becomes a preferred option over conditional assistance.*

Interior solutions have the following properties:

$$\frac{\partial \sum_{kj\neq 0} s^{j^*}}{\partial K} > 0 \; and \; \frac{\partial a^*}{\partial K} < 0 \,. \tag{7}$$

The implications of Proposition 2 largely encourage the use of unconditional social assistance, alongside other policies, in such circumstances. This is because, given the risk of death from the pandemic, focusing solely on the 'population impact' is insufficient. More universal measures, in the form of unconditional assistance, must be integrated into the strategy to adequately address the scale of the disaster.

4. Empirical Evidence

4.1. Statistical Analysis Model

Our empirical analysis focuses on examining how the severity of the COVID-19 crisis influences country-specific choices among different social assistance policies. The dependent variable categorizes these policy choices into four options: no policy, conditional policy, unconditional policy, and a combination of both policies. This framework allows us to test our hypotheses that crisis severity affects the likelihood of adopting unconditional social assistance (Proposition 1) and the preference for unconditional over conditional assistance (Proposition 2).

Given the categorical nature of the dependent variable, we use a multinomial logit approach to estimate the probabilities associated with each policy category relative to the reference category, 'no policy.' The severity of the crisis is our key explanatory variable, and we include control variables to account for other factors that may influence policy selection.

To address endogeneity concerns, particularly the potential for policy changes to influence the explanatory variables, we use lagged values in our model. This approach helps reduce bias by allowing the variables to predict current policy choices, while minimizing reverse causality.

While this method has its limitations, combining lagged variables with careful data selection and model specification provides a solid basis for our analysis

4.2. Data

Our sample is comprised of data from 47 countries, spanning the period from the initial diagnosis of COVID-19 to the commencement of the first vaccination campaigns, resulting in a total of 15,369 observations. These countries were selected based on the criterion that each had recorded over a thousand COVID-19 deaths by August 31, 2020.[5] This selection ensures that our analysis concentrates on countries significantly affected by the pandemic, where social assistance policies were both likely to be implemented and varied. The study period, from January 1, 2020, to December 14, 2020, deliberately excludes the influence of preventive measures such as vaccinations, thereby capturing the real-time evolution of policy responses. This high temporal granularity ensures our analysis is grounded in the actual progression of events rather than hypothetical scenarios.

We construct our dependent variable using the ‘Income Support (E1)’ measure from the Oxford COVID-19 Government Response Tracker (OxCGRT) dataset (Hale et al., 2021). This measure records whether governments provided direct cash payments to individuals who lost their jobs or were unable to work, categorizing support on a scale from '0' (no support) to '2' (coverage of 50% or more of lost salary).

To refine this variable, we reviewed each policy under E1 to classify the income support as conditional, unconditional, or a combination of both. This involved examining original sources and documentation to understand the conditions attached to payments. Payments made without stipulations were classified as unconditional, while those with specific requirements were labeled as conditional. Based on this classification, we created a categorical dependent variable with four groups: 'No Policy,' 'Conditional Policy,' 'Unconditional Policy,' and 'Both Policies,' capturing the diversity of government responses.

In terms of distribution, conditional policies were the most frequently implemented, accounting for 34.17% of the total observations. Unconditional policies were adopted in 24.62% of cases,

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[5] The countries included in the sample are: Algeria, Argentina, Bangladesh, Belgium, Bolivia, Brazil, Canada, Chile, China, Colombia, Dominican Republic, Ecuador, Egypt, France, Germany, Guatemala, Honduras, India, Indonesia, Iran, Iraq, Ireland, Italy, Japan, Kazakhstan, Kyrgyz Republic, Mexico, Morocco, Netherlands, Nigeria, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Romania, Russia, Saudi Arabia, South Africa, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom, United States.

while 33.82% of the sample did not implement any income support policy. Only 7.39% of the observations involved a combination of both conditional and unconditional policies. This distribution reflects the varied approaches taken by governments in response to the COVID-19 crisis, with a notable reliance on conditional support measures, when choosing between the two polices.

Our main explanatory variable, crisis severity (K), represents the monetized damage caused by COVID-19. We calculated this by multiplying the number of COVID-19 deaths, per million, by the value of statistical life (VSL). The VSL, as defined by Viscusi (2018), reflects the monetary tradeoff a worker accepts when facing an increase in fatality risk. However, VSL has been a subject of debate, with some, like Adler (2020), arguing that it is insufficient for evaluating regulations, especially in large-scale risks like pandemics. In response to these controversies, Sweis (2022) revisited the calculation of VSL in the context of COVID-19, refining it to better capture societal willingness to pay to reduce pandemic risks. Utilizing Sweis's data on VSL, we constructed a crisis index that is accurate and context-specific. To facilitate detailed analysis, we further divided K into deciles, allowing us to categorize crisis severity into ten equal groups.

We also include GDP per capita as a proxy for individual income, along with other control variables such as containment and closure measures, as these factors can influence the choice of social assistance policies. All variables in the dataset, except for GDP per capita, are recorded daily. GDP per capita is included as a static control variable, using the 2019 value consistently across the entire study period. This measure provides a baseline for economic capacity, allowing us to account for differences in countries' economic conditions that could influence social assistance policy decisions. Table 1 presents the definitions and sources for all variables used in this analysis, while Table 2 provides summary statistics.

TABLE 1 HERE

TABLE 2 HERE

4.3. Estimation Results

To validate our theoretical propositions on the optimal design of social assistance strategies during the COVID-19 crisis, we employ a multinomial logit model. The results, presented in Table 3, demonstrate that increasing crisis severity significantly influences the likelihood of governments adopting unconditional social assistance measures, supporting Proposition 1.

Proposition 2 is also confirmed, showing that higher crisis levels lead to a marked preference for unconditional support, or a combined approach with both conditional and unconditional measures. This reflects the logistical difficulties of targeting aid in severe crises, where swift distribution becomes paramount. The results further indicate that a mixed strategy balances conditional support in moderate crises, while unconditional support is more practical in extreme conditions.

TABLE 3 HERE

To illustrate these dynamics, Figure 1 presents the predictive margins for the probability of each policy type at different levels of crisis severity. The margins reveal that while conditional income support is initially favored, its probability fluctuates and eventually declines as crisis severity increases, likely due to the growing need for more inclusive and faster responses. In contrast, the probability of adopting unconditional support rises steadily, reflecting a strong preference for rapid aid deployment in the most severe situations. The combined approach of both conditional and unconditional support exhibits a more complex pattern, with its probability varying depending on the crisis level. This suggests that while a mixed strategy might balance immediate needs and conditional support in moderate crises, purely unconditional support becomes more practical in extreme conditions. Additionally, the likelihood of no policy implementation drops significantly as crisis severity increases, confirming that more severe crises prompt stronger government intervention, often favoring unconditional measures.

FIGURE 1 HERE

Our analysis also incorporates a range of control variables to account for other factors that might impact the adoption of social assistance policies. For instance, school closures are negatively associated with conditional income support (-0.04) but positively associated with the combined approach (0.08), suggesting that stricter school closures correlate with a lower likelihood of conditional support but a higher likelihood of implementing both forms of support together. Unconditional income support shows no significant relationship with school closures.

Canceling public events has mixed results: it is positively associated with conditional income support (0.03) and unconditional income support (0.05), indicating an increased likelihood of adopting these policies, but it is negatively associated with the combined approach (-0.07), suggesting a decreased likelihood of adopting both forms together. Restrictions on gatherings negatively impact the adoption of conditional income support (-0.04) and positively influence unconditional support (0.01), though the effect is minimal. The combined approach is positively influenced by restrictions on gatherings (0.02).

Closing public transport is positively associated with conditional income support (0.03), indicating an increased likelihood of adopting this policy. However, it negatively impacts the combined approach (-0.02), while having no significant effect on unconditional support (0.01). Stay-at-home requirements are associated with a small but significant decrease in the likelihood of adopting conditional support (-0.01). They have no significant effect on unconditional support (0.00) but significantly increase the likelihood of the combined approach (0.02).

Restrictions on internal movement have no significant effect on conditional support (0.00), a significant negative effect on unconditional support (-0.07), and a strong positive effect on the combined approach (0.06). International travel controls are negatively associated with both conditional (-0.01) and unconditional support (-0.03), indicating a decrease in the likelihood of adopting these policies individually. However, they have a strong positive association with the combined approach (0.06).

Lastly, GDP per capita in 2019 is positively associated with conditional income support (0.01) and has a small but significant positive association with the combined approach (0.00). It is negatively associated with unconditional support (-0.01). This indicates that wealthier countries may slightly prefer conditional or combined support strategies over purely unconditional approaches, likely due to their greater capacity and resources to implement more targeted assistance.

5. Conclusion

In this study, we develop a formal model to provide insights into the creation of optimal social assistance policies in response to the challenges posed by the COVID-19 crisis. Our theoretical investigation yields three key findings:

First, we advocate for a multifaceted approach that combines both conditional and unconditional assistance measures as the optimal response to the pandemic. This dual strategy ensures comprehensive support for affected populations, addressing immediate needs and longer-term stability.

Second, our results indicate that, as the expected severity of the crisis increases, governments should increasingly rely on unconditional assistance measures. This approach provides rapid and broad-based support, which is crucial during severe disruptions, especially when targeting individuals becomes challenging.

Third, we emphasize the critical importance of a government's capacity to design and implement policies effectively. In scenarios where accurately targeting affected individuals is difficult, a greater reliance on unconditional social assistance is necessary. This not only supports those in need but also helps contain the virus, thereby reducing the potential burden on healthcare systems.

Our empirical findings support our theoretical predictions, showing a strong positive association between crisis severity and the likelihood of adopting both conditional and unconditional policies, with a notable shift toward unconditional support as the crisis intensifies. This reflects the increased need for rapid and inclusive support in the face of significant economic and social disruptions, caused by the pandemic.

In summary, our findings underscore the importance of implementing unconditional assistance as an essential policy response during pandemic-induced crises, as relying solely on conditional assistance may prove inadequate in more severe instances. To support this approach, a robust budgetary system should be established, potentially involving temporary increases in universal credit levels, as suggested by Sawyer (2021). Notably, our analytical framework extends beyond the COVID-19 crisis and is particularly applicable to pandemics where the absence of immediate treatments or vaccines requires broad and timely social assistance interventions.

A key limitation in our analysis is that the available data only categorizes social assistance policies as conditional, unconditional, or a mix of both, without providing detailed insights into the scale, reach, or specific target populations of these interventions. This limitation underscores the need for future research to gather more granular data on the actual amount of assistance provided, the breadth of implementation, and the demographic characteristics of the recipients. Such comprehensive data would offer deeper insights into the design of social assistance policies.

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Appendix A

The first-order conditions for the maximization of W with respect to s^i and a are:

$$\frac{\partial\mathcal{L}}{\partial s^i} = \delta^i\left[\left(1-q^i\right)Mu^i f_1^i - f_1^i q_1^i\left(u^i + D^i\right)\right] - \lambda = 0 \quad \forall i$$

(A1)

and,

$$\frac{\partial\mathcal{L}}{\partial a} = \sum_{j=1}^{n} \delta^j\left[\left(1-q^j\right)Mu^j f_2^j k^j - f_2^j k^j q_1^j\left(u^j + D^j\right)\right] - \lambda K = 0$$

(A2)

where λ is the Lagrange multiplier, and Mu^i and Mu^j represent the marginal utility with respect to each argument of the utility function for individuals i and j, respectively.

Appendix B

As outlined in section 3, the condition $D^i \gg 0$ is a prerequisite for satisfying the second-order condition within the maximization problem (3). To elaborate further, two key determinants provide insights. Firstly, considering the determinant of the first n-1 bordered principal matrices:[6]

$$\begin{pmatrix} -f_{11}^1 q_1^1 - (f_1^1)^2 q_{11}^1 & \cdots & 0 & -1 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & -f_{11}^i q_1^i - \left(f_1^i\right)^2 q_{11}^i & -1 \\ -1 & \cdots & -1 & 0 \end{pmatrix}$$

the sign of this determinant is expected to alternate as $(-1)^i$ for $i = 2, \ldots, n$.[7] Secondly, when examining the determinant of the Hessian matrix:

$$\begin{pmatrix} -f_{11}^1 q_1^1 - (f_1^1)^2 q_{11}^1 & \cdots & 0 & -f_{12}^1 k^1 q_1^1 - f_1^1 f_2^1 k^1 q_{11}^1 & -1 \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & \cdots & -f_{11}^n q_1^n - (f_1^n)^2 q_{11}^n & -f_{12}^n k^n q_1^n - f_1^n f_2^n k^n q_{11}^n & -1 \\ -f_{12}^1 k^1 q_1^1 - f_1^1 f_2^1 k^1 q_{11}^1 & \cdots & -f_{12}^n k^n q_1^n - f_1^n f_2^n k^n q_{11}^n & \sum_{j=1}^{n}\left[-f_{22}^j \left(k^j\right)^2 q_1^j - \left(f_2^j\right)^2 k^j q_{11}^j\right] & -K \\ -1 & \cdots & -1 & -K & 0 \end{pmatrix}$$

[6] For the sake of simplicity in notation, we have omitted the D^i terms from the array elements.

[7] This is valid since all the diagonal elements, namely $-f_{11}^i q_1^i - \left(f_1^i\right)^2 q_{11}^i$, are negative. Consequently, the determinant of a bordered principal matrix equals the negative summation of the multiplication of $i-1$ diagonal elements.

this determinant is expected to carry the sign of $(-1)^{n+1}$.

It is necessary to assume that the value of life is sufficiently large for the second-order condition to be satisfied. A necessary condition for this is given by:

$$\left(f_{22}^{j}\left(k^{j}\right)^{2}q_{1}^{j}+\left(f_{2}^{j}\right)^{2}k^{j}q_{11}^{j}\right)\left(f_{11}^{i}q_{1}^{i}+\left(f_{1}^{i}\right)^{2}q_{11}^{i}\right)>2\left(f_{12}^{j}k^{j}q_{1}^{j}+f_{1}^{j}f_{2}^{j}k^{j}q_{11}^{j}\right)^{2}$$

(B1)

This condition is likely to be satisfied for any individual because f_{12}^{j}, the effect of each policy on the marginal relief of the other, is assumed to be very small.

Appendix C

Proof of Proposition 1: By finding λ from (A2) and substituting it into (A1), we obtain:

$$\delta^{i}\left[\left(1-q^{i}\right)Mu^{i}-q_{1}^{i}\left(u^{i}+D^{i}\right)\right]f_{1}^{i}K=\sum_{j=1}^{n}\delta^{j}\left[\left(1-q^{j}\right)Mu^{j}-q_{1}^{j}\left(u^{j}+D^{j}\right)\right]f_{2}^{j}k^{j}$$

(C1)

Let's denote the right-hand side as:

$$AECA\coloneqq\sum_{j=1}^{n}\delta^{j}\left[\left(1-q^{j}\right)Mu^{j}-q_{1}^{j}\left(u^{j}+D^{j}\right)\right]f_{2}^{j}k^{j}$$

(C2)

which stands for the Average Effect of Conditional Assistance. Therefore, based on (C1), we have:

$$\delta^{i}\left[\left(1-q^{i}\right)Mu^{i}-q_{1}^{i}\left(u^{i}+D^{i}\right)\right]f_{1}^{i}K=AECA\quad\forall i$$

(C3)

Now, given that $AECA$ does not vary significantly, and assuming large values of D^{i}, we can work with:

$$-\delta^{i}q_{1}^{i}D^{i}f_{1}^{i}K=AECA\quad\forall i$$

(C4)

From this, we derive the following comparative statics:

$$\frac{\partial s^{i^{*}}}{\partial K}=-\frac{-\delta^{i}q_{1}^{i}D^{i}f_{1}^{i}}{-f_{11}q_{1}^{i}-\left(f_{1}^{i}\right)^{2}q_{1}^{i}}>0$$

(C5)

$$\frac{\partial s^{i^*}}{\partial D^i} = -\frac{-\delta^i q_1^i f_1^i K}{-f_{11} q_1^i - (f_1^i)^2 q_1^i} > 0$$

(C6)

$$\frac{\partial s^{i^*}}{\partial \delta^i} = -\frac{-q_1^i D^i f_1^i K}{-f_{11} q_1^i - (f_1^i)^2 q_1^i} > 0$$

(C7)

$$\frac{\partial s^{i^*}}{\partial y^i} = -\frac{-f_1^i q_{12}^i}{-f_{11} q_1^i - (f_1^i)^2 q_1^i} < 0.$$

(C8)

It is important to note that the denominators are negative due to the properties of the relief function and the probability of death function, as previously discussed. These properties also help in determining the signs of the numerators.

■

Proof of Lemma 1: By finding λ from (A1):

$$\lambda = \delta^i\big[\big(1 - q^i\big)Mu^i f_1^i - f_1^i q_1^i\big(u^i + D^i\big)\big] = \delta^j\big[\big(1 - q^j\big)Mu^j f_1^j - f_1^j q_1^j\big(u^j + D^j\big)\big] \quad \forall i, j$$

(C9)

Then, using the corresponding indices in the summation of (A2) we may have:

$$\sum_{j=1}^{n} \frac{f_2^j k^j}{f_1^j} = \sum_{j=1}^{n} k^j$$

(C10)

This equality suggests that every policy must be used as much as it is effective. Using the form (6), we obtain:

$$\sum_{k^j \neq 0} \frac{s^{j^*}}{f_s} = \sum_{j=1}^{n} \frac{a^* k^j}{f_{ak}}$$

(C11)

based on which, $\sum_{k^j \neq 0} \frac{s^{j^*}}{a^* k} = \frac{f_s}{f_{ak}} n$ concludes the result.

■

Proof of Proposition 2: Rewrite equation (C10) as:

$$\sum_{j=1}^{n} \frac{f_2^j k^j}{f_1^j} = K$$

(C12)

Or alternatively:

$$\sum_{k^j \neq 0} \frac{\partial f/\partial a}{\partial f/\partial s^j} = K.$$

(C13)

Now, deriving comparative statics, we find that:

$$\frac{\partial a^*}{\partial K} = \sum_{j=1}^{n} \left(\frac{f_{22}^j}{f_1^j} - \frac{f_{12}^j f_2^j}{f_1^j} \right) k^j$$

(C14)

Likewise:

$$\frac{\partial \sum_{k^j \neq 0} s^{j^*}}{\partial K} = \sum_{j=1}^{n} \left(\frac{f_{21}^j}{f_1^j} - \frac{f_{11}^j f_2^j}{f_1^j} \right) k^j$$

(C15)

Therefore, if the two policies are complements, irrelevant, or even slightly substitutes, we may have the result, i.e., $\frac{\partial \sum_{k^j \neq 0} s^{j^*}}{\partial K} > 0$ and $\frac{\partial a^*}{\partial K} < 0$.

■

TABLE 1. Definition for All Variables.

Variable	Measurement
Income support policy:	
(1) No Income Support	This category indicates that no income support program was implemented in the country during the specified timeframe.
(2) Conditional Income Support	This category represents programs that provide income support subject to certain conditions, such as means-testing or employment requirements. Conditional income support is designed to provide income support to specific individuals and groups affected by COVID-19, not to all individuals.
(3) Unconditional Income Support	This category encompasses programs that offer income support without any specific conditions or requirements. Unconditional income support is aimed at facilitating lockdowns with a very wide range of recipients in each country, often for all individuals.
(4) Both Conditional and Unconditional Income Support	This category signifies the simultaneous provision of both conditional and unconditional income support programs by the country.
Crisis index	According to the level of the crisis, it is valued from 1 to 10. Deciles for the variable are created by multiplying deaths per million in value of a statistical life (VSL).
School closing	Closings of schools and universities 0 - no measures 1 - recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations 2 - require closing (only some levels or categories, e.g., just high school, or just public schools) 3 - require closing all levels
Cancel public events	Cancelling public events 0 - no measures 1 - recommend cancelling 2 - require cancelling
Restrictions on gatherings	Limits on gatherings 0 - no restrictions 1 - restrictions on very large gatherings (the limit is above 1000 people) 2 - restrictions on gatherings between 101-1000 people 3 - restrictions on gatherings between 11-100 people 4 - restrictions on gatherings of 10 people or less

Close public transport	Closing of public transport 0 - no measures 1 - recommend closing (or significantly reduce volume/route/means of transport available) 2 - require closing (or prohibit most citizens from using it)
Stay at home requirements	Orders to "shelter-in-place" and otherwise confine to the home 0 - no measures 1 - recommend not leaving house 2 - require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips 3 - require not leaving house with minimal exceptions (e.g., allowed to leave once a week, or only one person can leave at a time, etc.)
Restrictions on internal movement	Restrictions on internal movement between cities/regions 0 - no measures 1 - recommend not to travel between regions/cities 2 - internal movement restrictions in place
International travel controls	Restrictions on international travel 0 - no restrictions 1 - screening arrivals 2 - quarantine arrivals from some or all regions 3 - ban arrivals from some regions 4 - ban on all regions or total border closure
GDP	GDP per capita for 2019 (1000$)

Note: Data for GDP is sourced from the World Development Indicators (WDI). Data for the value of statistical life (VSL) is from Sweis (2022). The remaining variables are sourced from the Oxford COVID-19 Government Response Tracker (OxCGRT).

TABLE 2. Summary Statistics for All Variables.

Variable	Mean	Std. dev.	Min	Max
Income support policy				
(1) No Income Support	0.34	0.47	0	1
(2) Conditional Income Support	0.25	0.43	0	1
(3) Unconditional Income Support	0.34	0.47	0	1
(4) Both (Conditional & Unconditional)	0.07	0.26	0	1
Crisis index	5.52	2.93	1	10
School closing	2.02	1.21	0	3
Cancel public events	1.49	0.81	0	2
Restrictions on gatherings	2.63	1.66	0	4
Close public transport	0.77	0.8	0	2
Stay at home requirements	1.24	0.97	0	3
Restrictions on internal movement	1.16	0.91	0	2
International travel controls	2.485	1.42	0	4
GDP Per capita (1000$)	19.01	20.96	1.23	87.12

TABLE 3. Marginal Effects from Multinomial Logistic Regression.

Variables	Conditional Income Support	Unconditional Income Support	Both (Conditional & Unconditional)
Crisis Severity Levels:			
2	0.33***	0.01**	0.00*
	(0.02)	(0.00)	(0.00)
3	0.41***	0.14***	0.02***
	(0.02)	(0.01)	(0.00)
4	0.43***	0.21***	0.02***
	(0.01)	(0.01)	(0.00)
5	0.46***	0.26***	0.02***
	(0.01)	(0.01)	(0.00)
6	0.36***	0.44***	0.03***
	(0.01)	(0.01)	(0.00)
7	0.31***	0.53***	0.05***
	(0.01)	(0.01)	(0.01)
8	0.33***	0.51***	0.09***
	(0.01)	(0.01)	(0.01)
9	0.39***	0.38***	0.20***
	(0.02)	(0.02)	(0.01)

10	0.22***	0.66***	0.10***
	(0.01)	(0.02)	(0.01)
School closing	-0.04***	-0.01	0.08***
	(0.01)	(0.01)	(0.01)
Cancel public events	0.03**	0.05***	-0.07***
	(0.01)	(0.01)	(0.01)
Restrictions on gatherings	-0.04***	0.01**	0.02***
	(0.00)	(0.00)	(0.00)
Close public transport	0.03***	0.01	-0.02***
	(0.01)	(0.01)	(0.00)
Stay at home requirements	-0.01**	0.00	0.02***
	(0.01)	(0.01)	(0.00)
Restrictions on internal movement	0.00	-0.07***	0.06***
	(0.01)	(0.00)	(0.00)
International travel controls	-0.01***	-0.03***	0.06***
	(0.00)	(0.00)	(0.00)
GDP Per capita (1000$)	0.01***	-0.01***	0.00***
	(0.00)	(0.00)	(0.00)

Note: The significance levels (indicated by *** p < .01, ** p < .05, * p < .1). Standard errors, calculated using the delta method, are in parentheses. A time trend is included to account for temporal variation.

FIGURE 1. Predictive Margins of Social Assistance Policies at Different Levels of Crisis Severity