The perceived effectiveness and hidden inequity of postpandemic fiscal stimuli

Yaxin Zhang[a,1], Xinzhu Zheng[b,1], Daqian Jiang[c], Huilin Luo[a], Kaidi Guo[a], Xinke Song[a], and Can Wang[a,2]

Edited by Arild Underdal, Universitetet i Oslo, Oslo, Norway; received March 15, 2021; accepted February 23, 2022

The world has committed trillions in fiscal expenditures to reboot the economy in the post–COVID-19 era. However, the effectiveness and the equity impacts of current fiscal stimuli are not fully understood. Using an extended adaptive regional input–output model, we assess the short-term impacts (2020 through 2022) of feasible stimuli on the global economy and the labor market. Our findings show that the stimuli pledged by 26 countries, i.e., 2.4 trillion euros in total, are effective in keeping the recession short and shallow by saving 53 million to 57 million jobs (compared to the no-stimulus scenario). However, the stimuli exacerbate income inequity at the global scale if we define "equity" as those who suffer more from the pandemic should receive more assistance. Low-skilled workers in these countries, who suffer more from the pandemic than high-skilled workers, benefit 38 to 41% less from the job-creation effects of the current fiscal stimuli. As an alternative, low-carbon stimuli can achieve a balance between effectiveness and equity at the global level. Low-carbon stimuli save 55 million to 58 million jobs and decrease income inequality by 2 to 3% globally compared to the currently pledged stimuli. Country-level situations are more complicated, as modifying the current stimuli to achieve more "greenness" brings win–win in effectiveness and equity in some countries, while in the others, more greenness and equity are at the expense of less job savings. Our findings underscore the need to consider the overlooked trade-offs between effectiveness, equity, and greenness, both globally and nationally, when designing further postpandemic fiscal stimuli.

COVID-19 | low-carbon stimulus | effectiveness | inequality

Significance

Trillions in postpandemic stimuli present a prime opportunity to shape a climate-proof and equitable future. Herein, we compare the economic effectiveness and equity impacts of currently pledged stimuli and their green alternatives. Our findings reveal that while low-carbon stimuli are more effective (saving 1 million to 2 million more jobs) and more equitable (creating more jobs for low-skilled workers and decreasing global income inequality by 2 to 3%) than currently pledged stimuli on the global level, there are significant country-by-country variations. Some countries experience environmental benefits and equity at the expense of job savings as their sectoral composition and labor intensity change. Our study suggests the overall promise of green stimuli, but a careful country-specific approach in adoption.

The coronavirus disease 2019 (COVID-19) pandemic is intertwined with the challenges of economic recession, social inequality, and climate change (1). The lockdown restrictions that aim to reduce the infection rate have slowed down the global economy and, in particular, exerted disproportionate impacts on the low-income population. These people are often employed in labor-dependent industries that require face-to-face contact (e.g., the travel and restaurant industries) and have economically suffered the most from the distancing measures (2). According to a World Bank report (3), COVID-19 has put 71 million people into extreme poverty in the baseline scenario, and the number rises to 100 million in a downward scenario. Furthermore, income inequality acts as a multiplier that increases the spread and mortality rate of COVID-19 (4). People with lower income often have to work in environments with a higher level of exposure to the virus (5) and, if infected, have higher mortality rates due to the lack of affordable medical treatment and long-term care (6, 7). The disproportionate impact of COVID-19 on the low-income population is further exacerbated by the co-occurrence of the pandemic and extreme weather events, such as storms, floods, and wildfires (8), which often affect low-income populations more severely due to their lack of adaptation capacity (9). The self-reinforcing feedback loop reveals the necessity and urgency of balancing economic recovery, protection of low-income individuals, and climate adaptation during and after the COVID-19 pandemic (10).

So far, post-COVID fiscal stimuli have focused on rebooting the economy. More than 2 trillion euros have been committed, and the spending covers diverse areas from public health to education and research (11–13). However, the secondary impacts of these stimuli, namely, the climate change and equity impacts, are largely overlooked (14, 15). Researchers and policy makers have noted that carbon-intensive stimuli may irreversibly jeopardize climate change mitigation efforts, given the carbon lock-in effect of infrastructure (16). Green economic recovery, in contrast, can promote economic rebound while mitigating climate change in the post-COVID era (17, 18). Previous studies have evaluated the impacts of COVID-19 and fiscal stimuli on global emissions and emphasized the necessity of green recovery to achieve the goals of the Paris Agreement (14). Similarly, despite bearing the brunt of the pandemic, the poor and the

Author contributions: Y.Z., X.Z., and C.W. designed research; Y.Z., X.Z., and C.W. performed research; Y.Z. and X.Z. contributed new reagents/analytic tools; Y.Z., X.Z., and C.W. analyzed data; and Y.Z., X.Z., D.J., H.L., K.G., X.S., and C.W. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

[1]Y.Z. and X.Z. contributed equally to this work.

[2]To whom correspondence may be addressed. Email: canwang@tsinghua.edu.cn.

This article contains supporting information online at http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2105006119/-/DCSupplemental.

Published April 25, 2022.

Table 1. Scenario description

			Stimulus policy scenario		
	BAU	NS	CS	TS	LS
Pandemic	Without the pandemic	With the pandemic			
Scale of stimulus		Without stimulus	Announced in real-world stimuli		
Structure of stimulus			Real-world structure	Traditional sectors	Low-carbon sectors

vulnerable may not benefit equally from fiscal stimuli, further widening the existing gaps in income and well-being.

In this study, we comprehensively assess the effectiveness and equity impacts of the existing stimulus packages in 26 countries and compare them with those of traditional and low-carbon alternatives. We aim to answer the following questions: 1) How do the currently pledged stimuli perform with regard to economic effectiveness and social equity; and 2) comparatively, how do green stimuli perform using the same criteria? Through providing quantitative answers to these questions, we aim to help policy makers understand the relationships among economic growth, low-carbon transition, and social equity and make informed decisions in stimulus design.

Our assessment is enabled by an extended adaptive regional input–output (E-ARIO) model, which is widely used to estimate the economic impact of disasters such as floods (19, 20), earthquakes (21), and pandemics (14, 15) by placing constraints on labor or capital availability and quantifying the secondary impacts of these constraints along the supply chain. The model can also be used to simulate economic recovery processes by relaxing the capital and labor constraints and incorporating exogenous economic stimuli design into the settings. We construct the E-ARIO model based on the global input–output database EXIOBASE (22), which details the intermediate transactions among and the final consumption for 163 sectors in 49 countries, territories, and regions, and further incorporate big data for mobility (23–26) into the model as proxies for the strictness of a country's lockdown measures in the pandemic.

We find that while the currently pledged stimuli are effective in keeping the recession short and shallow, they also create risks of widening inequity, especially in developed countries, such as the United States and the countries of the European Union (EU). Moreover, the current stimuli could jeopardize climate-mitigation goals, as most of the countries have prioritized economic multipliers and deprioritized investments in green infrastructure. Low-carbon stimulus (LS) plans can restore the balance between greenness, economic effectiveness, and equity at the global level, providing a useful tool to address the intertwined challenges in the post–COVID-19 era. However, tradeoffs exist at the national level, as modifying the current stimuli to achieve more "greenness" and equity is at the expense of job creation in 18 of the 26 countries. We thus recommend a country-specific approach that considers effective stimulus, equitable distribution, and low-carbon transition in the stimulus design.

Results

Scenario Setting. To investigate the impacts of the COVID-19 pandemic and the stimulus plans on the global economy and employment, we developed five sets of scenarios (Table 1). The business-as-usual (BAU) scenarios, which describe the counterfactual economic dynamics without COVID-19 based on the economic projection for each country before the pandemic (27, 28), provide a baseline for the assessment. The nonstimulus (NS) scenarios, which describe the economic recovery process under the pandemic, but without the targeted fiscal stimulus, represent economic recovery dynamics driven solely by easing the lockdown restrictions and the social distancing measures. Additionally, we include three sets of scenarios representing feasible stimulus plans with the same scale, but different structures. As shown in Table 1, all three stimulus scenarios adopt the scale of real-world fiscal stimuli announced by 26 countries/regions, which are collected from the Oxford Global Recovery Observatory (OxGRO) (13). The three scenarios allocate the stimulus funds in different ways: The currently pledged stimulus (CS) scenarios allocate funds according to the structures announced by each country [stimulus structure information from the OxGRO (13)]; the traditional stimulus (TS) scenarios target traditionally advantageous industries, which are sectors that dominated each country's investments prior to the pandemic; and the LS scenarios allocate the stimulus funds to the low-carbon sectors recommended by the International Energy Agency (IEA) to meet the Paris Agreement goals (29). More detailed information on the assumptions, data, and methodology of the scenario design is available in *Materials and Methods* and *SI Appendix, Supplementary Methods*, section 2.

Disproportionate Effects of the Pandemic on Differently Skilled Workers. We first estimate the effect of the lockdown and social distancing measures during the pandemic on economic activities and the labor market. The estimates agree with existing knowledge that the pandemic caused drastic changes to the economy and employment (15, 30, 31), as Fig. 1 *A* and *B* shows. Associated with the sharp decline in economic output, the global labor demand decreased by 15 to 19% during 2020 through 2022, which equals a 268 million to 328 million decrease in job demand annually. This estimate is higher than the reported unemployment data from the International Labor Organization, which indicated that the job loss in 2020 was 255 million (32). A key reason for the differences between our estimates and theirs is that our model quantifies labor demand, the decrease of which does not necessarily lead to unemployment, but can also be reflected in the reduction of working time and wages. Our estimate shows that the most significant drop in labor demand was 43 to 63% during the peak of the pandemic (between late April and May 2020). Labor demand subsequently rose, but was still 27 to 45% lower than prepandemic levels by the end of August 2020. After August 2020, both the economic output and the labor demand showed a tortuous upward climb in 2021 due to multiple secondary lockdowns (33).

At the regional level, the United States, the EU, the United Kingdom, and Japan accounted for around half (41 to 52%) of the global economic losses during the pandemic, but the labor-demand losses in these regions accounted for only 12 to 15%

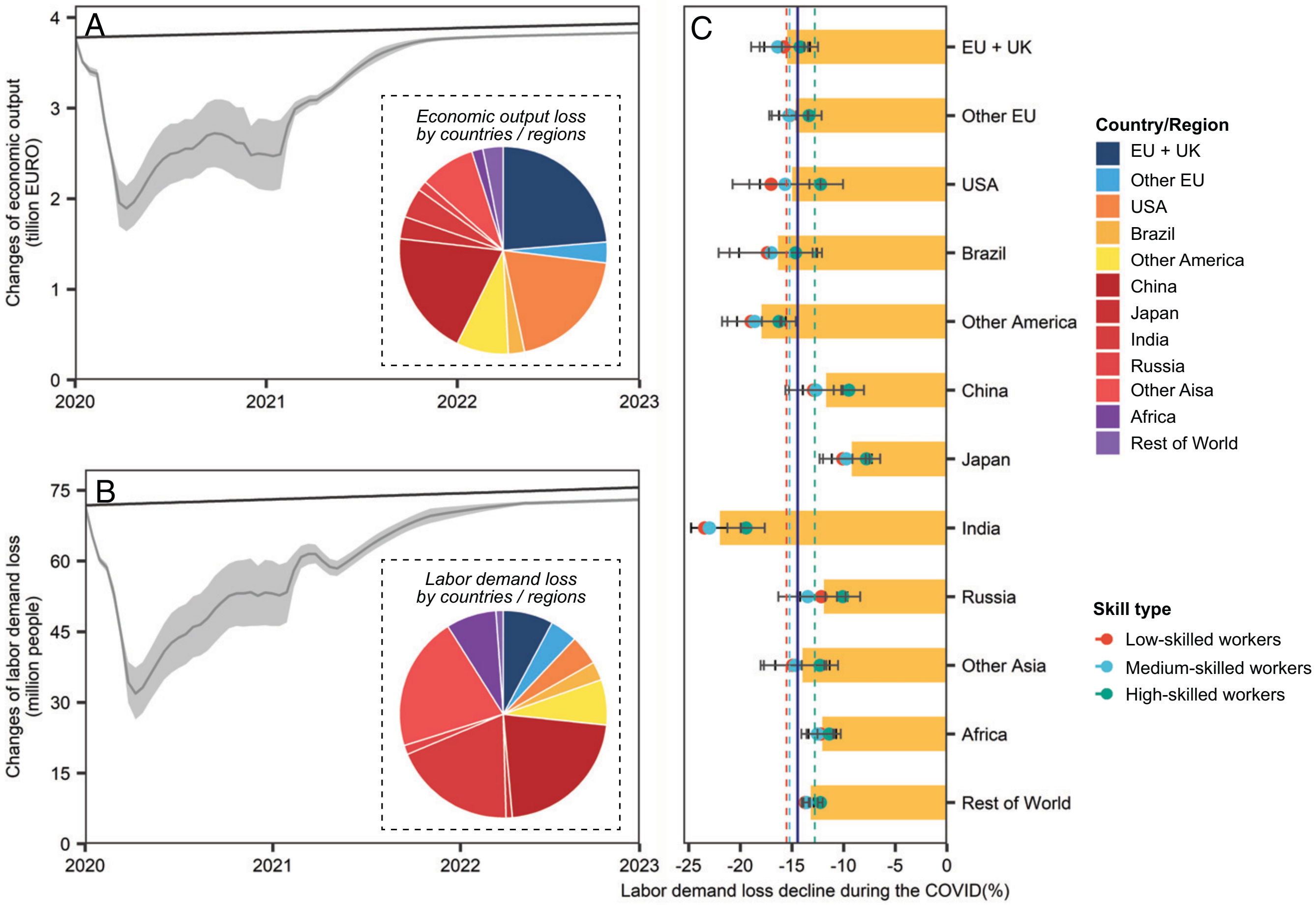

Fig. 1. The changes of economic output and labor demand under the COVID-19 pandemic. The graphs in *A* and *B* present the time-series changes of the COVID-19 on economic output and labor demand, respectively. The black line depicts the counterfactual BAU scenario without the pandemic. The gray line shows the NS scenarios, where the global economy was affected by the pandemic and recovered from easing distancing measures without additional stimulus. The pie charts in *A* and *B* show the loss of economic output and employment demand by country/region. The graph in *C* describes the impact of COVID-19 on labor demand by skill groups (displayed as points) and the average level (displayed as bars) in each region during the lockdown. The shaded areas and error bars represent the 95% CIs.

of the global total losses. The major global labor-demand losses came from Asian countries, especially China and India, which accounted for 57 to 77% of the global labor-demand decrease (169 million to 228 million people annually). The reason is in part because the industries in these regions are mainly labor-intensive sectors, and their workforce accounts for more than half of the global labor.

The pandemic exerts disproportionate effects on workers with different skill levels. Low- and medium-skilled workers [as defined in EXIOBASE 3.8.1 (22)] are more severely affected than high-skilled workers in terms of employment opportunities (Fig. 1*C*). Globally, low- and medium-skilled workers account for 83% of the global labor market, but suffered from 85 to 86% of the total loss in labor demand. The job demand for low-skilled workers was reduced by 12 to 16% (i.e., total loss of low-skilled job demand divided by the total low-skilled labor), whereas the demand for high-skilled workers was reduced by 11 to 14% (i.e., total loss of high-skilled job demand divided by the total high-skilled labor). Normalizing the losses to a per capita risk, the unemployment risks faced by low-skilled workers are significantly higher than those faced by high-skilled workers, as the *t* tests show. The uneven impact on workers with different skill levels confirms the knowledge that labor-intensive industries, which require more low-skilled workers, suffer more from social distancing measures during the pandemic (34, 35).

The inequity risk differs country by country (Fig. 2 and *SI Appendix*, Fig. S1). Assuming that the changes in income are proportionate to the reduction in labor demand, we use the Gini index and the Theil index, two widely used income-equality indices, to quantify the changes in income equality at both global and national scales (see *Materials and Methods* for details). The two indices show that the pandemic has exacerbated the income inequality by 1 to 7% globally. Interestingly, at the national level (Fig. 1*C*), the Gini index shows that Eastern European countries and the United States suffer from the highest increase in income inequality, with a 10 to 17% increase in the index, whereas the Theil index shows that China and South America suffer the most, with a 10 to 18% increase in income inequality. Despite the nuances in the extent of the inequality increase, which are reasonable, as the two indices describe different perspectives of the inequality (36, 37), these two inequality indices achieve an agreement that most of countries suffer an income-inequality increase during the pandemic.

Effectiveness of Stimuli on Flattening the Recession Curves. In addition to assessing the economic and equity impacts of the pandemic, we further assess the effectiveness of existing and feasible alternative stimuli. We find that all the stimulus plans (LS, TS, and CS scenarios) are effective, but their efficiency is relatively low, as one unit of fiscal stimuli only increases the

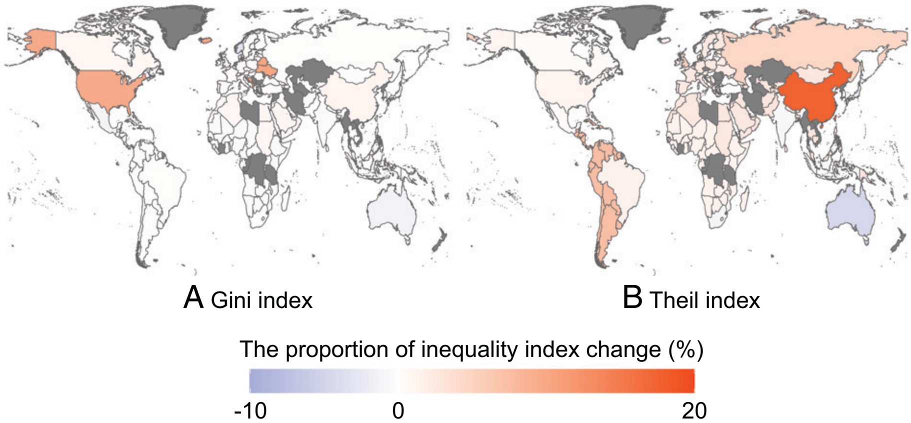

Fig. 2. Income-inequality change caused by the COVID-19 pandemic, as measured by the Gini index (*A*) and the Theil index (*B*). Orange indicates inequality increase, and blue indicates inequality decrease. Gray indicates countries/regions that are not included in this study due to data availability.

global gross domestic product (GDP) by 0.3 to 0.6 unit. Specifically, the stimuli announced by the 26 countries/regions—i.e., 2.4 trillion euros in total (i.e., 3% of the global GDP in 2019)—increase the global GDP by 1 to 2% of the 2019 level and reduce the labor-demand loss by 1 to 3% (from 15 to 19% in NS to 14 to 16% in LS, TS, and CS) by the end of 2022 (which is ∼50 million to ∼60 million jobs saved). The low effectiveness is consistent with previous studies, which reported that one unit (1%) of fiscal stimuli increases the global GDP by 0.1 to 0.8% during economic recovery (14, 38). One of the main reasons for the low effectiveness is that with strict lockdown measures, the global supply chain remains too fragile to transfer fiscal stimuli to production. This effect is exacerbated by the dependence on international trade in many countries—that is, even if some countries implement fiscal stimuli, the recovery of international supply chains will be slowed down by the absence of other countries' supply-chain and demand recovery (15).

Comparing the LS plans (LS scenarios) and the TS plans (TS scenarios) with the currently pledged stimuli (CS scenarios), we find that the LS and TS scenarios generate slightly higher multiplying effects on economic growth than the CS scenarios (by 8% at the global scale; Fig. 3). In terms of labor-demand impacts, the LS scenarios outperform the other two scenarios on the global level. The LS scenarios create 55 million to 58 million jobs, ∼3 million and 1 million more than the TS and CS scenarios, respectively. In other words, every million euros of fiscal stimulus create 22 to 25 jobs in the LS scenarios, ∼5% and 2% higher than those in the TS and CS scenarios, respectively.

There are considerable country-by-country variations in the job-boosting effects of the LS, TS, and CS scenarios. In the EU countries, the United Kingdom, the United States, Australia, Canada, Norway, South Africa, and India, the job-boosting effects of CS are significantly higher than TS and LS by 5 to 86%, whereas in Brazil, China, Japan, Mexico, Russia, and Switzerland, the labor-demand increase under CS is lower than TS and LS by 7 to 31%. The differences among countries are due to variations in the stimulus structure and the labor intensity of the industries receiving stimuli. More specifically, the money directed to labor-intensive industries in the CS scenarios in the former group of countries is 1.1 to 7.3 times the size of that in the LS and TS scenarios, whereas, in the latter group of countries, it is 24 to 41% lower than that in the LS and TS scenarios. It is worth noting that labor-intensive industries in various countries are different. For example, the labor-intensive industries in the EU and the United States are the education, research, and public health sectors, whereas those in India are the construction of traditional energy infrastructures.

At the country level, the advantages of LS plans over TS plans on job creation hold true in 14 of the 26 countries. In particular, the LS scenarios boost labor demand by up to 18% more than the TS scenarios in the United States. In contrast, the labor-demand increase stimulated by the LS scenarios is 1 to 7% lower than the TS scenarios in some of the European countries, Japan, and Brazil. This is because that in the United States, the key investment area in the LS scenarios is the renewable energy infrastructure, which generates secondary demand for labor-intensive construction sectors. In the other countries, the LS scenarios allocate less funds to the most labor-intensive retail sectors than the TS scenarios do.

Inequity Risks of Currently Pledged Stimuli on Employment. One important purpose of fiscal stimuli is to mitigate the inequity challenges brought about by the pandemic. With regard to this purpose, both the LS and TS scenarios perform better than the CS scenarios at the global scale (Fig. 3). In the TS and LS scenarios, low- and medium-skilled labor forces, which make up 83% of the labor market, receive 81 to 90% of the increase in job demand, while this number in CS scenarios is only 74 to

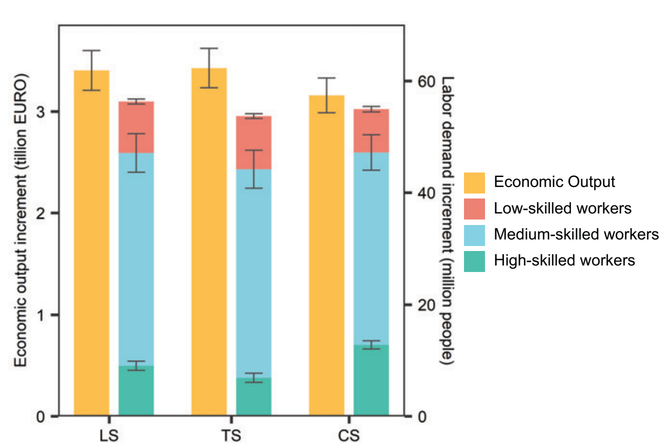

Fig. 3. The impact of fiscal stimuli on economic output and labor demand. The *x* axis is the three fiscal stimulus scenarios. For each scenario, the left and right bars are the increment of economy and labor demand (by labor skill levels) from 2020 to 2022, respectively. The NS scenarios are the reference point. Error bars represent the 95% CIs.

80%. Between the LS and TS scenarios, the LS are slightly more advantageous than the TS (Fig. 3), in that the LS create a higher total job demand, while maintaining a similar percentage of jobs accessible to low-skilled workers. Specifically, the total job demand for low-skilled workers in both the LS and TS scenarios is 9 million to 10 million, accounting for 15 to 19% of the total job-demand increment, but the increase in the high-skilled job demand is ∼9 million in the LS scenarios, 30 to 32% higher than that in the TS scenarios.

The demand for high-skilled workers in the LS scenarios is expectedly a result of investment in research, development, and innovation, which are high-skilled, labor-intensive sectors (39, 40). However, the demand increase for low-skilled workers in the LS scenarios contradict previous findings that the low-carbon transition benefits high-skilled workers at the expense of low-skilled workers (41, 42). A main reason for the difference is that our estimation focuses on the short-term effects of low-carbon investments, which rely on the construction of low-carbon infrastructure and drive up demand for labor-intensive, relatively low-skilled supporting industries, such as the steel, cement, and construction industries.

Compared with the TS and LS scenarios, the CS scenarios fare poorly in providing equitable job creation. The CS scenarios create 38 to 41% less low-skilled jobs than high-skilled workers globally (7 million to 8 million and 12 million to 13 million jobs for low- and high-skilled workers, respectively). Compared to the TS and LS scenarios, the CS scenarios create 40 to 90% more high-skilled jobs (4 million to 6 million more jobs) and 15 to 19% less low-skilled jobs (1.4 million to 1.8 million fewer jobs). This finding is further verified by the inequality coefficients: The Gini coefficients in the CS scenarios are increased by 2 to 3% compared with the TS and LS scenarios. The widening inequality gap in the CS scenarios is mainly because the currently pledged stimuli in most countries flow to sectors such as education and public health, where the demand for high-skilled workers is higher than that for low-skilled workers in general.

At the national level, the current fiscal stimuli (the CS scenarios) would exacerbate existing inequity in 23 of the 26 countries covered in this study, and 18 of the 23 countries are developed countries (Fig. 4). The inequality indices of the CS scenarios in these countries are 3 to 46% higher than in the TS and LS scenarios (*SI Appendix*, Table S1), whereas this trend is not found in the developing countries covered in this study. Such national heterogeneity is not only explained by the heterogeneity of the fiscal stimulus structure, but also by the differences of labor composition across countries. For example, although both developed and developing countries focus on education and public health sectors in currently pledged stimuli, there is a gap between the demand for high-skilled workers and low-skilled workers in these sectors. In developed countries, high-skilled workers in these sectors are 3 to 5 times the total of mid- and low-skilled workers, whereas in developing countries, high-skilled workers in these sectors are only 1 to 2 times the total of mid- and low-skilled workers.

The national heterogeneity also highlights the divergent trade-offs between greenness, equity, and effectiveness. For countries like those in the EU and the United States (Fig. 4*A*),

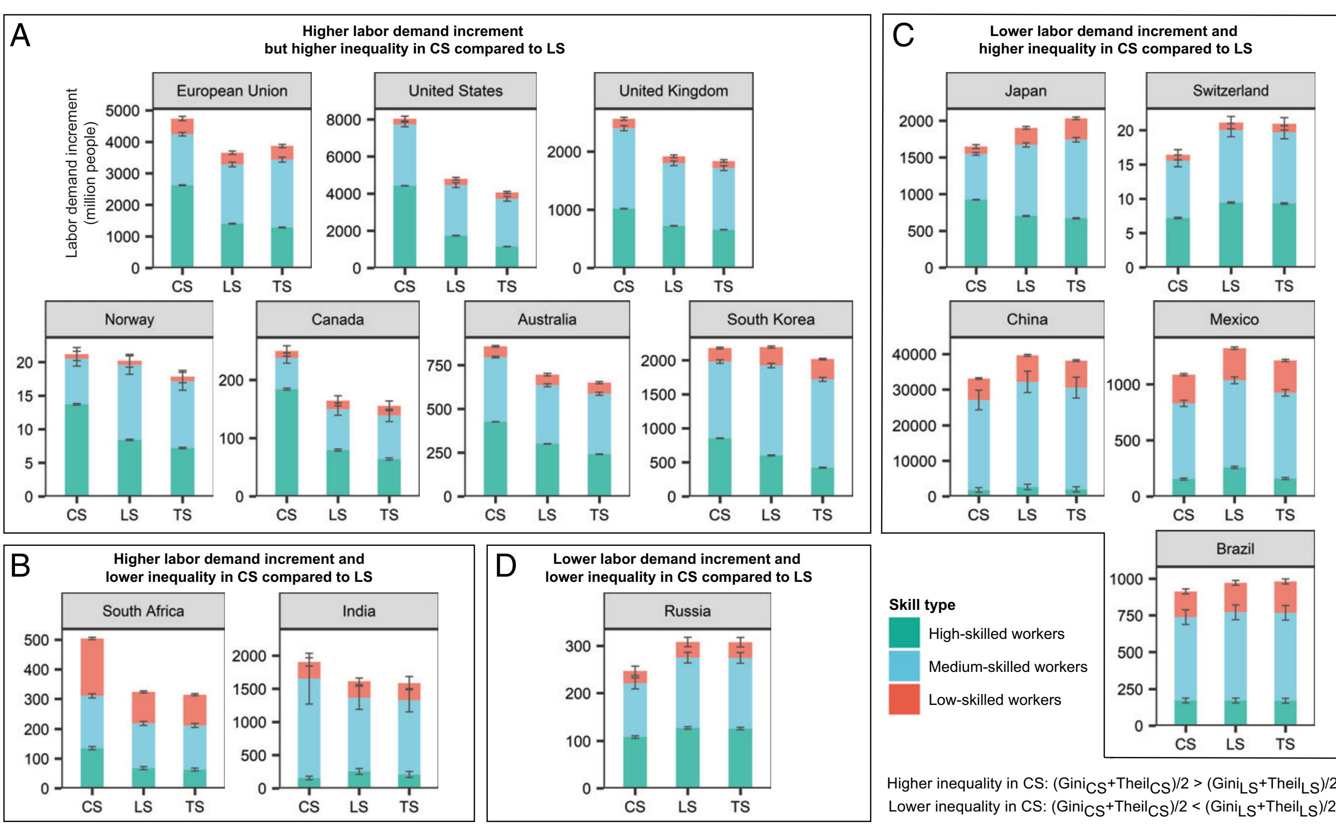

Fig. 4. The impacts of fiscal stimuli on labor demand and income inequality by country and skill level. Countries are categorized into four groups according to the change of labor demand and income inequality in CS scenarios relative to LS scenarios. Countries in *A* have a higher labor demand increase at the expense of less inequality in CS scenarios compared to LS scenarios. Countries in *B* have not only a higher effectiveness in saving jobs but also less inequality in CS than LS. CS scenarios in countries in *C* and *D* lead to a lower labor demand than LS. The inequality of countries in *C* in CS is higher than that of LS, while the situation of countries in *D* is opposite. EU in the graph in *A* represents 12 EU countries covered in this study (detail country/territory/region information is included in *SI Appendix*, Table S2). Error bars represent the 95% CIs.

changing the CS scenarios to LS scenarios will facilitate climate change mitigation and more equity at the expense of less effectiveness in terms of job creation. By contrast, in countries like Japan and China (Fig. 4*C*), modifying the currently pledged stimuli toward more greenness can achieve a balance between greenness, equity, and effectiveness.

Discussion

We assessed the effectiveness and potential inequity risks of existing and alternative feasible stimulus plans on the economy and employment in the post–COVID-19 era. A key finding is that all three stimulus plans are effective in mitigating the economic impact of the pandemic, which means that the "total pie" in all the stimulus scenarios increases. Their efficiency, however, is low, as the conversion ratio from fiscal funding to economic growth is less than unity. Sensitivity analysis (*SI Appendix*, Figs. S2–S7) suggests that there are two viable strategies to improve the low efficiency of fiscal stimuli: One is to coordinate the timing of stimuli with the relaxation of lockdown and distancing measures to eliminate supply-chain and final-demand limitations. Our sensitivity analysis shows that earlier stimuli are associated with more efficiency loss due to the stringent lockdown measures in the early months of the pandemic. The other is to increase the scale of stimuli to compensate for the efficiency loss (*SI Appendix*, Fig. S5). However, this pathway could be challenging due to budget limitations, especially in developing countries. Developing countries suffer more from the pandemic due to a sharp decline in international trade, fluctuating commodity prices, and rising borrowing costs in financial markets, and yet they have lower recovery capacities than high-income countries (18, 43, 44). International cooperation, including debt relief and foreign aid for low-income countries, could be a critical path to bridging the stimulus gaps in these countries.

Furthermore, the comparison among scenarios reveals that, in terms of economic recovery, the current stimulus plans pledged by the 26 countries are as effective as the LS and TS plans. However, the current plans distribute a large portion of fiscal funding to the public health sector and economic multipliers and place less emphasis on the low-carbon transition. Although these sectors have relatively low carbon intensities, funding to these sectors can jeopardize the long-term low-carbon transition, as renewable energy infrastructures, low-carbon buildings, and other low-carbon industries lose priority in the investment (11).

Another key concern regarding CS plans is that they create a higher risk of global inequity than LS and TS plans. A considerable quantity of fiscal funds is invested in sectors requiring high-skilled workers, while low- and medium-skilled workers, who suffer more from the pandemic, benefit less. This inequity is a reminder that the design and assessment of stimulus plans should carefully consider their structural effect on different populations. A comprehensive assessment framework is needed and should incorporate social equity as a major component. The indicators addressing social equity could include the impact of stimulus on different labor groups (by skill level, employment type, or sector) and different sectors.

LS plans, as a proposed alternative, show advantages in simultaneously promoting greenness and equity at the global scale. Compared with TS plans and CS plans, LS plans generate a bigger pie for all, with less risks in inequity increase. They strike a better balance among greenness, economic effectiveness, and income equity in our short-run analysis (2020 through 2022), facilitating multitarget management in postpandemic chaos. Previous concerns about structural unemployment in the low-carbon transition are not detected in the short run, as the transition requires investment in both traditional and high-tech economic multipliers that require the intensive input of low-skilled labor (e.g., the construction and manufacturing industry). While the structural unemployment in fossil fuel and other carbon-intensive sectors during the low-carbon transition may be inevitable in the long run, the short-run balance at least provides buffer time to prepare for a just transition and assists workers in these industries during the transition.

However, our findings also reveal the trade-offs between a larger pie and more equal slices for differentially skilled workers at the national level. In 18 of the 26 countries, modifying the currently pledged stimuli toward low-carbon ones leads to more equitable job distribution, but less total job savings. The country-level heterogeneity is, in part, explained by the variations in countries' sectoral labor intensity and composition change. The trade-offs are a reminder that policy makers need to take a detailed look at the country's specific situation to balance effectiveness, greenness, and equity. After all, fiscal stimuli provide a lever to catalyze a sustainable transition toward a climate- and equity-positive future in the post-COVID era. To enable this transition, both greenness and equity should be incorporated into the stimulus packages (45).

We acknowledge the following limitations of our research. First, our equity assessment focuses only on employment equity, which does not include secondary and long-term equity impacts. For example, climate change may affect social equity, given its disproportionate impacts on public health, and low-carbon stimuli can contribute to alleviating this inequity. Such long-term effects are not included in our short-term analysis. Furthermore, our estimation of labor demand and wage changes in the pandemic focuses only on the impacts of social distancing measures. Other influencing channels, such as permanent labor-demand loss due to virus infection, are not included in the simulation. Last, our fiscal stimulus simulations adopt the Keynesian fiscal stimulus, which mainly solves the unemployment problem driven by insufficient final demand. More stimulus measures, including distributive policies, can be assessed in future studies.

Materials and Methods

Impact Assessments Based on E-ARIO Model. We adopt the Adaptive Regional Input–Output (ARIO) model (20, 46) to simulate the economic impact of the COVID-19 pandemic and different fiscal stimuli. The ARIO model is one of the most effective tools to simulate the short-term economic shock of disasters and postdisaster economic recovery (14, 15, 19, 47). It characterizes how the impact of the disaster on labor market and final demand is transmitted through the supply chains and thereby enables the estimation of both direct and induced impacts. The model has been used to simulate how the supply chains are affected by COVID-19 lockdown measures and how the fiscal stimuli affect global emissions (14, 15). Our model further improves the previous versions (15) in the following aspects: 1) The ARIO model is soft-linked with various fiscal stimulus scenarios along with final-demand changes; 2) an employment-impact module is integrated to simulate employment demand and income changes under the pandemic; and 3) parameters are set and calibrated according to the latest available data, including big data on traveling and lockdown measures, to reflect the realistic impact of the pandemic. The ARIO model after these adjustments is named E-ARIO.

Estimating the economic impact. The E-ARIO model contains four main modules–the Production Function Module, the Intermediate Input Module, the Labor Supply Module, and the Demand Module–and runs iteratively. The Production Function Module describes the economic process of firms based on the

Leontief Production function. The Intermediate Input Module represents the input storage of firms, which will receive the allocation of goods from other firms to restore their inventories. Labor supply is depicted in the Labor Supply Module, affected by the strictness of lockdown during the pandemic and economic stimulation policies in the recovery processes. The Demand Module shows the demand from both consumers and firms, which will impact the production.

In each iteration period (i.e., time step), the firms in sector i make optimal production decisions ($IOX^r_{i,t}$) based on intermediate products ($IOZ^r_{i,t}$), labor availability ($IOL^r_{i,t}$) , and previous orders by consumers and other firms ($OD^r_{i,t-1}$) in the Production Function Module:

$$IOX^r_{i,t} = \min\left(\frac{IOZ^r_{i,t}}{z^r_i}, \frac{IOL^r_{i,t}}{l^r_i}, OD^r_{i,t-1}\right), \quad [1]$$

where z^r_i is the intermediate input coefficient (quantity of input for each unit of output) for sector i in region r. The labor-input coefficient (quantity of labor for each unit of output) is represented as l^r_i. Since the pandemic is a sudden shock with little time for companies to respond, the relations of production cannot change elastically in the short term. Therefore, the intermediate input and labor coefficients remain constant. They are calculated based on production at the initial state ($t = 0$):

$$z^r_i = \frac{IOZ^r_{i,0}}{IOX^r_{i,0}}, \quad [2]$$

$$l^r_i = \frac{IOL^r_{i,0}}{IOX^r_{i,0}}. \quad [3]$$

The calculation of $IOZ^r_{i,t+1}$, $IOL^r_{i,t+1}$, and $OD^r_{i,t}$ is elaborated on in the Intermediate Input Module, the Labor Supply Module, and the Demand Module.

During this time step, goods produced by firms are allocated to consumers and other firms, satisfying the final demand and forming new inventories. Meanwhile, new orders are placed by customers and firms, which are used to determine production and employment demand for the next time step. A detailed description of the equations and parameters is provided in *SI Appendix*, *Supplementary Methods*.

Unexpected occurrences of the pandemic and lockdown measures have a short-term impact on inventory stocks, labor availability, and demand. As a result, firm production drops down sharply, resulting in a drop in economic output at the macro level. As lockdown restrictions are eased in the post-COVID period, the number of workers coming to work can increase gradually. Furthermore, fiscal policy may boost economic growth by stimulating the final demand. Firm output can progressively recover under the effect of these two factors, and the macroeconomic and employment impact of fiscal stimulus can be evaluated over time. This discrete-time dynamic procedure can simulate the spread of exogenous shocks (i.e., the pandemic) and the recovery of supply chain in the economic network, both from the firm and household sides, which will provide a brief overview of the economic system equilibrium (15).

Estimating the employment impact. To explore the employment impact of the recovery processes, we calculate the labor demand and sectorial income as follows:

$$Employment^{r,k}_{i,t} = Em^{r,k}_i \times IOX^r_{i,t}, \quad [4]$$

$$Wage^{r,k}_{i,t} = If^{r,k}_i \times IOX^r_{i,t}, \quad [5]$$

where $Employment^{r,k}_{i,t}$ is the labor demand for the k th labor type by sector i in region r during period t, and $Wage^r_{i,t}$ is the wage of the k th labor type in sector i in region r during period t. $Em^{r,k}_i$ is the demand coefficient (amount of labor required for each unit of economic output) for the k th labor type, and If^r_i is the income coefficient (income provided by each unit of product). $IOX^r_{i,t}$ represents the economic output of sector i in region r at time t. The two factors are calculated based on the initial state ($t = 0$):

$$Em^{r,k}_i = \frac{Employment^{r,k}_{i,0}}{IOX^r_{i,t}}, \quad [6]$$

$$If^r_i = \frac{Wage^r_{i,0}}{IOX^r_{i,t}}, \quad [7]$$

where $Employment^{r,k}_{i,0}$ is the demand for the k th labor type in sector i, and $Wage^r_{i,0}$ is the initial wage provided by sector i.

Based on the sectoral average income, we categorize sectors into three groups: the low-income (40% of the workers), medium-income (40%), and high-income (20%) groups (31–33). Low- and medium-skilled workers account for more than 97% of the low-income sector, whereas high-skilled workers account for ∼40% of the high-income sector.

We calculate the average wage by dividing the total income by the initial labor supply and define the change in the average wage relative to the initial average wage (i.e., the initial state without the pandemic) as the wage loss. This is because the total labor supply remained constant in the short term, and the change in wages due to the pandemic mainly results from the loss of employment opportunities.

Estimating income inequality. We quantify income inequality with two indicators, namely, the Gini index and the Theil index. The Gini index is a measure of the distribution of income across a population (37, 48, 49). The Theil index is a measure of income disparity between individuals or regions, calculated using the concept of entropy in information theory (50).

The Gini index is calculated as:

$$Gini = 1 - \frac{\sum_g AI_g \times r_g}{0.5 \times AI_{max}}, \quad [8]$$

where AI_g is the gth worker group's average income, while r_g is the proportion of the gth worker group in all workers. AI_{max} represents the average income of the worker groups with the highest income. A higher value of the Gini index indicates a greater income gap and increased social inequality.

The Theil coefficient is calculated as:

$$T(\alpha) = \frac{1}{(\alpha^2 - \alpha)} {}_{g=1} \left[\left(\frac{Q_g}{P_g}\right)^{\alpha} - 1\right], \quad [9]$$

where P_g is the proportion of the population in different groups, and Q_g indicates the proportion of the group income. $T(\alpha)$ measures the match between population share and income share. α reflects the degree of aversion to inequality, with smaller values representing higher aversion to inequality.

Scenario Setting. We establish five sets of scenarios based on three factors: whether there is a pandemic, whether there is a stimulus plan, and the structure of the fiscal stimulus (Table 1). The first set of scenarios are the counterfactual BAU scenarios, which are designed to reflect the economic situation without the pandemic. They provide the baseline for evaluating the impact of the pandemic. The second set of scenarios are the NS scenarios, which include the pandemic, but exclude any fiscal stimulus. They provide the baseline to compare the impact of different stimulus policies.

Three more sets of fiscal stimulus scenarios are designed by varying the structure of stimulus with the same scale of stimulus. The CS scenarios are based on the real-world stimulus scale and structure announced by the countries. Stimulus data are collected from OxGRO (13). These stimulus policies are classified and grouped according to sectors in the E-ARIO model to present the current committed fiscal stimulus structure for each country (Dataset S1). The TS scenarios and LS scenarios follow the same scale of stimulus as CS, but allocate the funds to traditionally advantageous industries and low-carbon industries, respectively. We set the stimulus structure for the LS scenarios based on the low-carbon investment structure in the IEA report (29) (Dataset S2). The TS scenarios allocate the funds to the traditionally advantageous sectors of each country, which are sectors that dominated the country's investments prior to the pandemic. The top 40 sectors from each country are used in TS (sensitivity analysis on the sector numbers is presented in Dataset S2). In all the scenarios, fiscal stimuli are started at the end of the first round of the pandemic. Since the timing of fiscal stimulus is a potential influencing factor, sensitivity analysis is conducted, and the results are presented in *SI Appendix*, *Supplementary Discussion*. *SI Appendix*, *Supplementary Methods*, section 2 contains further information on the assumptions, data, and technique used in the scenario design.

Key Assumptions, Data Sources, and Uncertainty Analysis.

Key assumptions and data sources for model simulation. *Global supply chain and employment/income impacts.* We simulate the global supply chain using the latest available data from the input–output database EXIOBASE 3.8.1 (51). The data describe the economic flows among 163 sectors in 49 countries, territories, and regions (*SI Appendix*, Tables S2 and S3), where the 44 countries/territories account for 86% of the global GDP in 2019 (52), 80% of the global CO_2 emissions in 2018 (53), and 61% of the global labor supply in 2019 (54). The five regions cover the rest of the world. We also use the satellite matrix data from EXIOBASE 3.8.1 (51) to estimate employment and income impacts. In the database, both sectoral employments and incomes are divided into three categories: the high-, medium-, and low-skilled workers. Based on this categorization, this study discusses the impact on the demands of different types of workers under various fiscal stimuli plans.

Time frame and time step. Since the model predicts short-term impact, and there is the possibility that the pandemic might end with worldwide vaccination (35), we design the model with a time frame of 3 y, from January 2020 to January 2023. As described earlier, the model operates iteratively, and the iteration period (i.e., the time step) is set to 2 wk, considering the practical response time of enterprises and the development trend of the pandemic (55–57). This time step is consistent with other related studies, which also use adaptive input–output models to evaluate pandemic and disaster footprints (14, 15, 19–21, 46, 47, 58–60).

Pandemic lockdown measures. Since lockdown measures are altered with the periodic fluctuation of the pandemic, the strictness of lockdown measures and their economic shock should be estimated in combination with different pandemic phases. Hence, the 3-y time frame is divided into two periods. The first one is the strict lockdown period from January 19, 2020, to May 23, 2021, where we use real-world lockdown data from actual policies (61) and mobility data. For this phase, we use the lockdown-strictness data from Google Community Mobility Report (37) and the Oxford COVID-19 Government Response Tracker (13) (until May 22, 2021) to check whether residents work from home or at the workplace. The Google Community Mobility Report (37) also reports transportation to other destinations (retail store, grocery, and pharmacy; parks; transportation hubs; and residential areas), which are used to calibrate the demand data during the pandemic. Since the Google Community Mobility Report provides limited data of China, we use Baidu Map data to calibrate China's measures during the pandemic period (38–40). The second period is from May 23, 2021, to January 13, 2023, where we assume the labor supply and final demand recover at a certain rate, according to related research and the historical trend (14, 15, 23). All parameters for model calibration and simulation, as well as the data sources, are presented in *SI Appendix*, Tables S2–S4.

Key assumptions and data sources for scenario setting. Our main assumptions in establishing scenarios include the counterfactual economic growth for the BAU scenario; economic recovery in the NS scenario, driven by easing lockdown measures and proxied by the recovery rate of labor availability and final demand; and the timing of fiscal stimuli. First, we assume that in the counterfactual BAU scenario, where COVID-19 does not exist, economic output will grow at the expected rate of growth, and the growth rate for each country remains the same within the entire process. Similar scenario settings have been used in Shan et al. (14) and Kikstra et al. (62). Second, the NS scenario describes both the process of the economy being shocked by the pandemic and economic recovery as the lockdown measures are lifted. We assume the gradual economic recovery without additional fiscal stimulus as lockdown measures are eased and removed through the gradual recovery of labor supply and final demand, which is measured by the labor-recovery rate and the demand-recovery rate. According to the Google Community Mobility Report, the recovery rate of the labor supply and final demand in most countries after the first round of the pandemic is 2 to 4% per week. We thus establish the NS scenarios based on this estimation. Three fiscal stimulus scenarios follow the basic establishment of the NS scenarios. We also identify the sensitivity of these two parameters and further establish subscenarios for the NS scenario and policy scenarios based on the estimated parameter ranges. Third, fiscal stimulus timing is a key parameter that influences the results of policy scenarios. In the scenario simulation, we assume that fiscal funds will be allocated into sectors at the end of the first round of lockdown measures; thus, the stimulus timing varies among different countries. Different stimulus timing is also set in the sensitivity analysis and considered in the subscenario design.

Sensitivity and uncertainty analysis. Changes in the model-calibration data, the scenario-design parameters, and the model-configuration parameters could result in uncertainty in our estimates. These factors are grouped into *SI Appendix*, Table S5 and examined individually. We find that the results are sensitive to the lockdown strictness, the total amount of fiscal stimulus, the recovery rate of the labor supply, the final-demand recovery rate, and the timing of the fiscal stimulus. We then conduct an uncertainty analysis by combining orthogonal experimental design (OED) with the scenario design. OED is an effective method for arranging and analyzing multifactor interactions. It presents full factorial scenarios and is widely used in scenario design to perform uncertainty analysis (14, 15, 63, 64). We include 72 subscenarios (the lockdown strictness [2] $\times$ the total amount of fiscal stimulus [3] $\times$ the recovery rate of labor supply [2] $\times$ final-demand recovery rate [2] $\times$ the timing of the fiscal stimulus [3]) in each set of scenario groups (1 BAU scenario, 1 NS scenario, and 3 policy-stimulus scenarios). The parameter ranges are summarized in *SI Appendix*, Table S6. The methods and results for these uncertainty analyses are presented in *SI Appendix*, *Supplementary Discussion*.

Data Availability. The code, data, and data source for this research can be accessed at Zenodo (https://doi.org/10.5281/zenodo.6326444). All study data are included in the article and/or supporting information. Previously published data were used for this work (12, 13, 15, 22–27, 29, 65, 66).

ACKNOWLEDGMENTS. We acknowledge funding by National Natural Science Foundation of China Projects 71904201 and 72140002; the National Key R&D Program of China (2017YFA0603602); and the Science Foundation of China University of Petroleum, Beijing (No. 2462022YXZZ005).

Author affiliations: [a]State Key Joint Laboratory of Environment Simulation and Pollution Control, School of Environment, Tsinghua University, Beijing 100084, China; [b]School of Economics and Management, China University of Petroleum–Beijing, Beijing 102249, China; and [c]Department of Civil, Construction, and Environmental Engineering, University of Alabama, Tuscaloosa, AL 35487

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