The Welfare Impact of the COVID-19 Pandemic: An Analysis of the Philippine Labor Market using the CGE-Microsimulation Approach

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Abstract

Global exogenous shocks usually challenge the capacities of these economies to cushion their welfare impacts. The COVID-19 pandemic is a prime example of such a shock. Such shocks translate to macroeconomic slowdowns, labor market contraction, and decreases in welfare. We take the case of the Philippines and assess the labor market and welfare effects of the pandemic at its onset, and whether cash assistance would have reversed these decreases in welfare.

Using a recursive CGE-microsimulation strategy, we find that for 2020, the pandemic would have reversed the country's improvements in poverty headcount if no transfers are given to affected households and workers. However, while broader coverage of transfers may have tempered the reduction in welfare, possible leakages may ensue. Thus, in future similar circumstances, policymakers may face a trade-off between implementing a cost-efficient policy and a broad coverage of assistance for affected households.

Keywords: COVID-19 pandemic, computable general equilibrium, microsimulation, poverty, cash transfer

I. Introduction

The lessons from the Coronavirus Disease 2019 (COVID-19) pandemic inform policy options for future similar scenarios. Its onset disrupted lifestyles and livelihoods globally as governments restrict mobility and economic activity in their respective countries since 2020. Unfortunately, these caused severe downturns in the global economy, which cut the gains in reducing extreme poverty globally. In fact, the World Bank (2020; 2021) projected that about 71 million people around the world may have been pushed into extreme poverty due to the pandemic. This is the first global increase in extreme poverty recorded since 1998. Meanwhile, inequality among socioeconomic status, age, gender, ethnicity, and geography is expected to have worsened as well (Blundell et al. 2020).

Locally, the Philippines implemented lockdown measures of varying stringencies in March 2020. While the pandemic and these policy measures have contributed to the decline in gross domestic product (GDP) by -9.6% in 2020, the pandemic may have also reversed the country's recent gains in poverty reduction. Prior to the pandemic, poverty incidence among the population declined from 23.5% in 2015 to 16.7% in 2018 (Philippine Statistics Authority 2019). A decline in GDP and a sharp increase in unemployment from about 5% in 2019 to 10% by 2020 would have pushed more people down the poverty line. This is supported by the fact that about 7.4 to 11.3 million households have members that are highly vulnerable to unemployment and income losses due to industry closures and lockdown restrictions (Ducanes, Daway-Ducanes, and Tan 2021). However, we cannot determine the severity of the welfare effects of the onset of the pandemic due to the lack of official statistics during the said period. Furthermore, the theoretical and empirical scholarship that pin the changes in the labor market as the main drivers of the declines in welfare remain limited (Reyes et al. 2020; Albert et al. 2020; United Nations Development Programme 2021).

With the foregoing facts, we simulate the welfare impacts among Filipino households during the onset of the pandemic in 2020, and in turn, determine whether policy interventions such as cash transfers have reversed any of the pandemic's welfare-reducing effects on households. While the focus of the paper is on the 2020 scenario of the pandemic, the findings of the study offer insights on the welfare effects and policy options for similar scenarios in the future.

In the literature, majority of pandemic-related studies remain as ex-ante analyses (Albert et al. 2020; Reyes et al. 2020; United Nations Development Programme 2021; Keogh-Brown et al. 2020a; Laborde, Martin, and Vos 2021). In terms of empirical strategy, these studies fail to capture the linkages between the economic impacts of the pandemic and welfare through the labor market. Furthermore, while the Philippine Statistics Authority (PSA) released information on the increase in poverty incidence from 2018 to 2021, the lack of regular tracking of household income and expenditure data made the welfare effects of the initial onset of the pandemic initially unavailable. We fill these gaps in the growing body of COVID-19 CGE literature by providing an ex-post evidence of the macroeconomic and labor market impacts of the pandemic in 2020 as means of tracking the welfare effects of the pandemic on a more shorter-term basis.

We assess the impacts of the pandemic, its associated behavior, and corresponding policies on the labor market and on poverty using the 2018 Philippine social accounting matrix that is calibrated in a recursive CGE model based on Rutherford (1999; 1995). We then link the general equilibrium changes in the labor market to a non-parametric Monte Carlo-like microsimulation model (Vos and Sanchez 2010) that generates the poverty and inequality measures at a national level.

We also develop a theoretical framework that links the pandemic and poverty by extending the labor market model of Pissarides (2000; 1985) using the analytical solution in Gottschalk and Danziger's (1985) poverty model to establish theoretical credence to the empirical strategy. The labor market model assumes that there are matching frictions between the unemployed and job vacancies; therefore, firms and workers must invest their time and resources to establish a match. Thus, we posit that given a negative economy-wide shock, there is a proportional decrease in production across jobs regardless of productivity levels. This is absorbed in the labor market by an increase in unemployment and a decrease in expected real wages. At the same time, the decrease in expected wages in the economy increases the poverty as there are more people that fall below the economy's poverty threshold. Meanwhile, the cash transfers temper the overall increase in poverty in the face of a negative economic shock.

We note that assessing the COVID-19 pandemic using the CGE-microsimulation strategy fails to distinguish the direct health effects of the pandemic, and the second- and subsequent round effects of the pandemic borne from behavioral and policy responses. However, since the literature suggests that majority of the economic losses due to the pandemics are borne from the second- and subsequent round effects (de Lara-Tuprio et al. 2022; Keogh-Brown et al. 2010), the limitation does not constitute a loss of generality in the results of the study. With this, we collectively refer to direct health impacts of the pandemic scenario, the associated behavior from the pandemic, and the policy responses of the government as the impacts of the COVID-19 pandemic.

The succeeding sections of this paper are organized as follows: section 2 reviews the empirical and theoretical literature, section 3 lays down the theoretical framework, section 4 tackles the methodology, section 5 presents the results and discussions of the simulations, and section 6 concludes the paper.

II. Literature Review

While the empirical links between pandemics and household welfare have a consensus that such shocks have negative effects on poverty, the theoretical links between these variables remain loosely explored. Meanwhile, nuances in the empirical evidence show that the gravity of the impact of pandemics and their associated policies on the macroeconomy and on welfare hinges on the economic structure and initial endowments in a country.

The Economy, Downturns, and Poverty in Theory

The theoretical literature on the determinants of poverty, especially with respect to economic downturns, pandemics, and unemployment, remains incoherent as existing theoretical studies only link these variables in isolation. Poverty is heavily determined by nutrition levels, income levels and distribution, the cost to access education and healthcare services, and the depletion of natural resources in the case of households dependent on natural capital (Gottschalk and Danziger 1985; Albin 1970; Ray 1988; Narain, Gupta, and van't Veld 2008).

Poverty trap models may also be useful in analyzing the link between economic downturns, pandemics, and welfare. Ghatak (2015) categorizes poverty trap models into two: friction-driven traps and scarcity-driven traps. He argues that for market imperfections to cause poverty traps, other conditions such as different production technologies and restrictions on inheritance must exist. Meanwhile, scarcity-driven traps show that since the poor lack resources, they do not tend to save and invest. Therefore, the study suggests employing cash transfers to mitigate the implied barrier to save.

Bonds et al. (2010) offer a unique model that shows the persistence of poverty due to infectious diseases. By extending a compartmentalized epidemiological model to capture the level of income of individuals, where income is inversely related to disease prevalence, Bonds et al. (2010) argue that escaping the trap must involve either direct interventions against disease prevalence or changes in labor productivity to increase the conversion rate from a healthy labor force to a higher income level.

The above theories on poverty generally assume the exogeneity of incomes, or the simultaneity of incomes with other environmental variables such as infectious diseases. These theories do not endogenize the changes in incomes within an economic arena, such as the labor market. The labor market theories of Pissarides (2013; 2000) and Diamond (2011) lend theoretical coherence to changes in income following exogenous economic scenarios such as negative economic shocks. By assuming a labor market with search frictions between the unemployed and job vacancies, their models show that any change in aggregate economic output will be simultaneously absorbed by wages on one hand, and unemployment on the other.

However, while these labor market models can be applied into pandemic scenarios where these cause declines in output, they fall short in accounting for the welfare effects of the changes in wages and unemployment following an economic shock. With this gap, the empirical literature provides insights on the macroeconomic impacts of pandemics, and how these are transmitted into household welfare.

Macroeconomic Impacts of Pandemics

The empirical literature on the impacts of a pandemic fall in two areas: the macroeconomic impacts and the household welfare impacts of pandemics. Moreover, while pandemics affect both developed and developing countries, Noy et al. (2020) and Djankov and Panizza (2020) highlight that developing countries tend to face difficulties in weathering the economic effects of the pandemic due to pre-existing high levels of poverty and inequality, large share of informal workers, low technological advancement, and more. These nuances are further justified by the differences in the economic structure of these countries as depicted in their respective Input-Output Tables and social accounting matrices (SAMs), which underlie the data structure of the economic analysis.

Prior to the COVID-19 pandemic, the studies of Chou, Kuo, and Peng (2004) and Rodriguez et al. (2007) show how local economies would have declined due to the simulated contractions in the manufacturing and services sectors during the severe acute respiratory syndrome (SARS) outbreak of 2003 and the avian influenza outbreak in the early 2000s. Meanwhile, for the 2009 H1N1 pandemic, Keogh-Brown et al. (2010) show that the H1N1-related deaths and infections will cause varying degrees of contractions in the economies of United Kingdom, France, Belgium, and the Netherlands, depending on the severity of the pandemic in terms of clinical attack rates and case fatality rates. The United Kingdom has also experienced a welfare loss worth 0.37% to 4.99% of its GDP.

The pre-COVID studies above contribute to the discussion on which types of impacts contribute greatly to the economic losses that countries experience. Keogh-Brown et al. (2010) argue that school and business closures increase GDP losses by threefold. Crowd avoidance contracts labor supply as well, thus contributing to contractions in the macroeconomy (Geard et al. 2020; Keogh-Brown et al. 2010).

However, the COVID-19 pandemic is distinct from the outbreaks of the recent decade not only due to its widespread transmission, but also because of the policies enacted by various governments globally which have repercussions on their corresponding economies. The implementation of lockdown strategies by governments affected both the supply- and demand-sides of national and global economies. In Ghana, Amewu et al. (2020) find in a SAM-based analysis, using a single round effect of the pandemic, that the industry and services sectors will decline by 26.8% and 33.1%, respectively. Such contractions will be majorly caused by the closures of non-essential sectors. Finally, higher income households lose more income relative to lower income households as the former tend to suffer more from the reductions in wage compensation in the severely affected formal sectors of the economy (Amewu et al. 2020; Almeida et al. 2020).

The United Nations Development Programme (2021) employs a similar SAM-based analysis to study the effects of COVID-19 in the Bangsamoro Autonomous Region in Muslim Mindanao (BARMM) in the Philippines. They find that the regional GDP will contract by 3.2% due to final demand shocks. Meanwhile, while the agricultural sector is simulated to have the largest contraction in absolute terms, it does not experience a large percentage decline relative to the other sectors in the region.

Porsse et al. (2020) support the conclusion on the robustness of agriculture in their CGE study in Brazil. By simulating a temporary shutdown of non-essentials and a decline in labor supply, they find that a 3-month lockdown will have still made the agricultural sector robust from the economic impacts of COVID-19. However, Djifack, Dudu, and Zeufack (2020) show a different picture in sub-Saharan Africa, citing that the sharp contractions in agriculture and services cause disproportionate impacts on the poor. However, such findings might have been influenced by the researchers' usage of Ebola-based counterfactuals on COVID-19.

Other CGE studies investigate the effects of the pandemic on other severely hit sectors such as tourism (Pham et al. 2021) and public transportation (Betarelli Junior et al. 2021). Pham et al. (2021) note that a reduction in tourism demand in Australia will cause a reduction in income of tourism laborers. The large spillover effects of the contraction in demand and output of the tourism industry will justify an increase in government support for the said sector. Meanwhile, a 1% reduction in the recovery rate of the public transport sector in Brazil will result to a -0.03% deviation over GDP growth in six months (Betarelli Junior et al. 2021).

The studies above typically impose the shocks through final demand channels or through the reduction of labor supply due to government restrictions. Moreover, social distancing shocks aggravate the final demand shocks caused by the COVID-19 pandemic (Geard et al. 2020). In fact, evidence from the United Kingdom suggests that government restriction policies tend to contribute more to the total losses in GDP in contrast with direct losses such as deaths and isolation (Keogh-Brown et al. 2020b).

While focus on labor supply has been furthered by using epidemiological variables, other studies (Verikios et al. 2012; Laborde, Martin, and Vos 2021) model their CGE studies to account for capital shocks. These include strategies of lowering the substitutability between labor and capital or assuming that there is excess capacity on capital. Furthermore, the studies highlight that second-and subsequent round effects of the pandemic have a more significant share in economic losses than direct losses.

While it is clear that pandemics cause economic slowdowns, the studies above offer limited insight on the distributive and welfare effects of such crises. Thus, to capture the macro and micro effects of pandemics, recent studies use also use partial equilibrium and microsimulation models, and to some extent, link the latter models with CGE strategies.

Welfare Effects of Pandemics

Simulations and analyses on the welfare effects of pandemics hinge on how health crises affect the incomes of individuals and their respective households' welfare. Unfortunately, illnesses and deaths caused by pandemics affect the capability of households to accumulate assets and move out of poverty (Barrett and McPeak 2006). These serve as justification for establishing safety nets to reduce people's needs to adversely liquidate their assets for consumption smoothing (Barrett and McPeak 2006).

In India, Dev (2020) argues that universal social protection during the COVID-19 pandemic is beneficial to cushion the impact for the vulnerable low- and middle-income households, and those who lost their jobs. Meanwhile, Bhorat, Oosthuizen, and Stanwix (2021) provide evidence from South Africa that a broad coverage of transfers that also include middle-income households may not be as cost-efficient as increasing the disbursed amount to a targeted low-income segment of the population.

In the Philippines, it is estimated that about 7.4 to 11.3 million households have members that are highly vulnerable to be unemployed due to the strict lockdown restrictions at the onset of the pandemic (Ducanes, Daway-Ducanes, and Tan 2021). Most of the highly vulnerable are employed in the private sector, self-employed in non-agricultural line of businesses, or are employers themselves. When actualized, these vulnerabilities translate to income losses and poverty magnitude increases, which may be mitigated with social assistance to the bottom 70% to 90% of households (Reyes et al. 2020; Albert et al. 2020).

It should be noted that for the case of pandemics and their associated policy interventions, welfare impacts may course through several channels such as employment, prices, and public goods, among others (Djankov and Panizza 2020; Amewu et al. 2020). To account for these interdependences of markets and sectors in the economy amidst health shocks and government interventions, CGE-microsimulation models may be used. However, while such macro-micro models for the COVID-19 pandemic remain sparse, existing studies agree that the pandemic will worsen poverty and inequality, and government stimuli will be beneficial to curb such effects. For instance, the simulations in South Africa show that poverty rates increase and female-headed households experience more severe declines in income (Chitiga et al. 2021; Chitiga-Mabugu et al. 2021). However, income inequality will contract because richer households tend to be worse off due to the bigger contraction in their incomes that come from formal sector employment and transfers from abroad.

Meanwhile, in a static top-down model by Laborde, Martin, and Vos (2021), they show that as the global GDP contracts by 5% following the reduction in labor supply across countries, this will increase global poverty by 20%, global rural poverty by 15%, poverty in sub-Saharan Africa by 23%, and in South Asia by 15%. The increase in rural poverty follows the pandemic's impact on the agricultural sector, where it has experienced smaller direct effects from the pandemic. However, they have also simulated a shift in consumption towards grains following the expected supply chain disruptions due to the pandemic.

Nechifor et al. (2021) has localized the above findings in Kenya, where the country will experience high unbalanced diet despite existing measures from the government that ensures that food sufficiency and adequacy do not fall. As such, 1.3% of households will fall below the calorie intake thresholds. In Ethiopia, Nechifor et al. (2020) also show that food poverty in the country will increase by 5% in total population should government interventions remain absent. Employment will also have dropped by 18.2% in 2020 and 9.4% in 2021. However, these can be reversed through production subsidies.

Gaps in the Literature

There is a growing but limited body of knowledge concerning the welfare effects of the COVID-19 pandemic. While the empirical evidence above agrees that any pandemic scenario will cause economic downturns and welfare declines, the empirical strategies fail to trace the causalities between macroeconomic impacts of pandemics and their subsequent welfare impacts through the changes in the labor market. We fill this gap by developing an empirical strategy that links the macroeconomic results from the CGE model with the household database using a labor market-focused microsimulation strategy.

The theoretical literature illustrates a similar picture where the determination of the poverty effects of economic downturns caused by exogenous factors such as a pandemic is not clearly endogenized in theoretical models. We address this gap in the next section by proposing that negative economic shocks are translated into poverty effects through the dynamics of a labor market with imperfections and matching frictions.

III. Theoretical Framework

This section develops a model that addresses the gap in the theoretical literature by linking a negative economic shock scenario with household welfare through the labor market. The literature suggests that the macroeconomic effects of the COVID-19 pandemic, together with the associated behavior and policies, are translated into worsening household welfare through labor displacement and unemployment. Thus, to satisfy this observation, we construct a model that extends the labor market model of Pissarides (2000; 1985) using the analytical solution of Gottschalk and Danziger's (1985) poverty model to illustrate the poverty effects of a negative economic shock.

By operationalizing the effects of the pandemic as negative output shocks through a proportional decline in productivity, we show that wages decline across all jobs. However, the decline of wages tends to be lesser than the decline in output as some are absorbed by an increase in unemployment. As average income in the economy goes down, poverty is expected to increase. Appendix A elaborates the theoretical framework.

Unemployment Rates and Wage Determination

Following Pissarides (2000; 1985), we assume the following conditions: (1) firms open or close jobs base on their expected profit on job vacancies and occupancies, (2) workers search for these vacancies in a decentralized labor market, (3) there is no voluntary unemployment in the labor market, and (4) the matching in the labor market is not instantaneous as there are information asymmetries, frictions, and individual heterogeneities among firms and workers.

The heterogeneities in the fourth assumption includes heterogeneities in skill level of workers and, more importantly, the heterogeneities of job productivities. We represent the heterogeneities of job productivities in the labor market as an idiosyncratic productivity parameter x that draws from a cumulative distribution function $G(x)$, where x is in the interval $[0,1]$. If firms have reservation productivities R, then $G(R)$ represents the probability that productivity lies below the reservation productivity. The flow into unemployment is determined by the arrival of shocks to occupied jobs at a Poisson rate λ. With this, let the change in unemployment rate be given by,

$$\dot{u} = \underbrace{\lambda G(R)(1-u)}_{\substack{job \\ separation}} - \underbrace{\theta q(\theta) u}_{job\,matches} \tag{1}$$

where $q(\theta)$ is the rate of filling up vacancies and is a decreasing function of the vacancy-unemployed ratio θ, the market tightness indicator.

From Equation (1), if the labor market is at the steady-state equilibrium $\dot{u} = 0$, then Equation (1') shows that unemployment is dependent on the arrival of shocks λ, market tightness θ, and reservation productivity R,

$$u = \frac{\lambda G(R)}{\lambda G(R) + \theta q(\theta)} \tag{1'}$$

Meanwhile, we assume that firms rely on profit maximization to decide whether new jobs will be created, or whether occupied jobs will be destroyed. On the other hand, workers get to match with these vacancies given the prevailing matching technologies in the labor market. These assumptions serve as the foundation for wage determination. Specifically, the interaction of firms and workers are founded on Nash bargaining. Therefore, wage rates $w(x)$ must maximize the weighted product of workers' and firms' return from a job match. If $W(x)$ is the expected returns of employed workers, U is the expected returns from unemployment, $J(x)$ is the expected returns of a firm from an occupied job, and V is the expected returns of a firm from a job vacancy, then wage rates must satisfy,

$$w(x) = \arg\max[W(x) - U]^{\beta}[J(x) - V]^{1-\beta} \tag{2}$$

where β is the bargaining strength of workers. Using the condition in Equation (2), we derive the wage equation below that maximizes the weighted net returns of workers and firms from a job match,

$$w(x) = (1-\beta)b + \beta p(x + c\theta) \tag{3}$$

Equation (3) highlights that wages depend on market tightness θ, output or general productivity p, and idiosyncratic job productivity x. The equation also shows the reason why wages do not absorb changes in productivity fully, that is, it is dependent on unemployment returns b.

Unemployment and Wages during Negative Shocks

The previous section establishes the determinants of unemployment and wages in the labor market. From there, this section shows that wages decline and unemployment increases simultaneously with a proportional decrease in job productivities. The empirical strategy operationalizes the economic shocks associated with COVID-19 as a change in value added of sectors. We represent this in the theoretical framework as an increase or decrease in parameter p. With this, market tightness decreases and reservation productivity increases with a proportional decrease in productivity p. This causes wages to decrease and unemployment to increase simultaneously.

Graphically, Figure 1 shows that with a decline in general productivities, the level of unemployment increases from point E_1 to point E_2. This is due to the decrease in market tightness which rotates θ_1 to θ_2. However, the increase in reservation productivity shifts the Beveridge curve outward from A to B, which gives a higher unemployment at point E_3.

<FIGURE 1 HERE>

Meanwhile, given the change in proportional productivity, expected wages follow at the same direction,

$$\frac{\partial E[w(x) \mid x \geq R]}{\partial p} = \beta E[x \mid x \geq R] + \beta c \left[p \frac{\partial \theta}{\partial p} + \theta\right] > 0 \tag{4}$$

Thus, in a specific economic scenario where the shock causes a proportional downturn on all job productivities, average wages are expected to decline as well.

Poverty Effects of Downturns

The previous section highlights that expected wages goes down and unemployment increases with a widespread economic downturn scenario. Using these results, we show that poverty increases by assuming a poverty threshold T. A person is poor if their income-to-needs ratio as determined by wages and unemployment returns is,

$$I^* = \frac{w(x) + b}{T} < 1 \tag{5}$$

It can be shown using Equations (4) and (5) that any proportional decrease in productivity caused by an economic phenomenon shifts the income-to-needs ratio at the same direction as wage rates.

With this, let any poverty index be determined by,

$$P = \int_{-\infty}^{T} f[w(x), b, \boldsymbol{m}] dw(x) db \tag{6}$$

where f is the general probability distribution function of wages and nonmarket activities, and $\boldsymbol{m}$ serves as the vector of stochastic parameters from $w(x)$ and b. Following Gottschalk and Danziger (1985), we assume that I^* has a displaced lognormal distribution. With this, we represent the income-to-needs ratio I^* as,

$$z = [\ln(I^* + k) - \mu]/\sigma \tag{7}$$

where k is a displacement factor, $\mu = E[\ln(I^* + k)]$, and $\sigma = Var[\ln(I^* + k)]$. With Equation (7) adopting a standard normal distribution $\phi(z)$, then the poverty index can be defined in terms of its normalized income-to-needs ratio,

$$P = \int_{-\infty}^{h} \phi(z)dz \tag{8}$$

such that $h = [\ln(1 + k) - \mu]/\sigma$.

Through Equation (8), we show that the poverty index is a decreasing function of $E[I^*]$ (See proofs in Gottschalk and Danziger (1985) and Appendix A). Therefore, poverty increases if negative economic shocks affect outputs through a proportional decrease in productivity in jobs. But with the presence of transfers, this increase may be tempered (See Appendix A).

The theoretical framework establishes a link between a negative economic shock and poverty through the changes in unemployment and wages. To provide empirical evidence for the framework in the Philippines' case during the COVID-19 pandemic, we propose an empirical strategy where the change in general productivities in the economy is operationalized as the change in value added across different production sectors. The strategy hinges on a CGE-microsimulation framework that models the transmission between a decline in general productivities and the corresponding poverty effects through the changes in the labor market.

IV. Data and Empirical Framework

Data Description

We use the 2018 SAM and the 2018 Family Income and Expenditure Survey-Labor Force Survey (FIES-LFS) as the databases of the CGE and the microsimulation strategies of the study, respectively. Correspondingly, these databases allow my empirical framework to be nationally representative at the macro level, i.e., at the level of production sectors, final demand, intermediate demand, as well as at the household level.

We construct the SAM using the 80-sector 2018 Input-Output Table (Philippine Statistics Authority 2021). The 80 sectors are aggregated into a 50-sector matrix to account for the limitations in the other SAM data sources. Other data sources that are used to construct the SAM at the 2018 level include the 2018 Income and Outlay accounts from PSA, the Flow of Funds and Balance of Payments from the Bangko Sentral ng Pilipinas (BSP), the Philippine central bank, and the tax data from the Bureau of Internal Revenue (BIR), the revenue generation agency of the Philippine government.

Finally, the FIES is a nationally representative household survey that gathers information on income, expenditure, and poverty thresholds (Ericta and Fabian 2009). The PSA constructs the 2018 FIES-LFS by making the 2018 FIES as the rider survey for the January 2019 LFS. The second volume of the 2018 FIES disaggregates the household account in the SAM into income decile groups.

Methodology

In this section, we elaborate the top-down non-parametric CGE-microsimulation method of the study. However, unlike the conventional top-down non-parametric models which only use changes in wage rate and consumption to derive poverty and inequality, we use the iterative non-parametric microsimulation model of

Vos and Sanchez (2010) as the “bottom” model to capture the changes in the labor market and derive welfare parameters at a 95% level of confidence.

Prior to implementing the CGE-microsimulation model, we construct the 2018 SAM which serves as the database for the recursive CGE model. We disaggregate labor inputs into low-skilled and high-skilled wage labor based on workers' secondary educational attainment. Households are also classified according to their total income deciles. With this, Table 1 shows the essential accounts of the 2018 SAM.

<TABLE 1 HERE>

Upon constructing the SAM, we conduct the following three-tiered approach for the CGE-microsimulation implementation: (1) the CGE model is calibrated, (2) the counterfactual scenarios are run recursively in the CGE model, and (3) the microsimulation model is implemented for all outputs of the recursive implementation.

The CGE model has a mixed complementarity problem (MCP) specification, which uses the dual problems of consumer and producer theory (Rutherford 1999). The minimization problem of consumers and producers generates the expenditure function and the unit cost function, respectively. The demand of households and firms can be extracted from these functions using the Shephard's Lemma. These produce the Hicksian demand functions of consumers and the input demand functions of firms.

Following Rutherford (1999), should all economic activities and economic institutions be subjected to this derivation, the following equilibrium conditions are generated as a square system of weak inequalities:

1. The zero-profit condition, where production costs must be greater than revenues for commodities and utility, else, no production takes place;
2. The market clearing condition, where supply must be greater than demand, else the market shuts down and prices are set to zero, and;
3. The income balance condition, where equilibrium expenditure should not exceed equilibrium income for all economic institutions.

In general, these equilibrium conditions govern the transaction flows in the economy, as seen in Figure 2. In these flows, the domestic output can then be either exported to the external market or be used as part of domestic consumption. Moreover, the domestic commodities are aggregations of the domestic supply and the imports, which are consumed by households, firms, the government, or as intermediate inputs.

Meanwhile, the representative households, the representative firm, the government, and the external market receive incomes, and conduct savings and investment activities. Households and firms receive pay taxes to and receive transfer from the government. Furthermore, the production and consumption functions are aggregated using the constant elasticity of substitution (CES) or the constant elasticity of transformation (CET) functional form, which follow either the Leontief or the Cobb-Douglas specification.

<FIGURE 2 HERE>

Upon calibrating the model using the flow above, we conduct a recursive implementation to simulate the equilibrium conditions per quarter in 2020 relative to the baseline by changing the value-added parameter in the model. We calculate the general equilibrium changes in the labor market from the general equilibrium sectoral output and employment-output ratio using the 2018 FIES-LFS and National Income

Accounts. Furthermore, we derive a value for the fixed labor force using the employment rate from the 2018 FIES-LFS and the general equilibrium employment level to relax the limitation of the CGE model that is programmed to assume full employment only.

From this, we link the CGE model to the microsimulation model using the general equilibrium changes in the labor market. We use the recursive version of the top-down non-parametric microsimulation model of Vos and Sanchez (2010). In a recursive environment, each run imposes the counterfactual shocks on the baseline scenario. Using the 2018 FIES-LFS, the poverty and distributive effects of the pandemic are generated by letting per capita income for every household (ypc_H) with n members be,

$$ypc_H = \frac{1}{n_H}\left[\sum_{i=1}^{n_H} \underbrace{yp_{Hi}(\varphi, c_{H_i})}_{\substack{labor\ income \\ of\ member\ i}} + \underbrace{yq_H}_{\substack{non-labor \\ income\ of\ household}}\right] \tag{9}$$

The labor income of a household member is a function of labor market conditions φ and household member heterogeneities c_{Hi}. The per capita income is converted in terms of consumption using the marginal propensity to consume.

Meanwhile, the labor market is a function of unemployment per skill level (U); three sectors of employment (S) consisting of the agriculture, industry, and services sectors; wage labor category (O); the renumeration structure (W_1); the level of renumeration (W_2); and skill composition of the employed population (M):

$$\varphi = \varphi(U, S, O, W_1, W_2, M) \tag{10}$$

Thus, the sequential changes in the labor market from φ to φ^* through the shifts in the six (6) labor market variables cause changes in the labor income of household members, which in turn, affect the income per capita of households.

The model assigns a random number to determine changes in employment status, labor market segment, and labor incomes. From here, each individual is grouped and ranked according to their categories and segments in the labor market based on their random numbers. The Foster-Greer-Thorbecke (FGT) and Gini indices are determined given changes in the labor market variables from the baseline scenario to each counterfactual quarter (See Vos and Sanchez (2010) for the simulation all the labor market variables). The FGT index uses the PHP 25,813 national poverty line from the Philippine Statistics Authority (2020b).

The simulations are repeated 30 times because of the randomized process, yielding a 95% confidence interval for mean of the poverty and inequality parameters. Formally, Equation (11) shows the computation of the indices from the baseline to the counterfactual scenarios following the changes in the labor market using the per capita household income or consumption,

$$\Delta^{sim} I(ypc_H) = \sum_{s=1}^{6}\left[\bar{I}_s^{sim}(ypc_H) - \bar{I}_{s-1}^{sim}(ypc_H)\right] \tag{11}$$

where $\bar{I}_s^{sim}(ypc_H)$ corresponds to the respective means of each index for all iterations, $\bar{I}_0^{sim}(ypc_H) = I(ypc_H)$ is the baseline scenario, $\bar{I}_1^{sim}(ypc_H) = \bar{I}\left(U_j^*, S, O, W_1, W_2, M\right)$ simulates the change in unemployment at t^*, $\bar{I}_2^{sim}(ypc_H) = \bar{I}\left(U_j^*, S^*, O, W_1, W_2, M\right)$ simulates the cumulative effects in the change in unemployment and in the composition of sectoral employment. $\bar{I}_3^{sim}(ypc_H)$ to $\bar{I}_6^{sim}(ypc_H)$ follow the same logic as above.

Counterfactual Design

The literature shows that second- and subsequent round effects of the pandemic have a more significant share in economic losses in contrast to direct labor losses due to deaths and illnesses (Smith, Keogh-Brown, and Barnett 2011; de Lara-Tuprio et al. 2022; Keogh-Brown et al. 2020b). Thus, we use secondary shocks of the COVID-19 pandemic in the Philippines to capture its general equilibrium effects through the changes in value added for all quarters of 2020.

<TABLE 2 HERE>

After the COVID-19 shock simulations, we conduct three policy simulations for cash transfers (Bhorat, Oosthuizen, and Stanwix 2021): the limited amelioration scenario for households at the bottom 30%, a boosted scenario equal to twice the limited disbursement, and the broadened scenario for the bottom 60% of households and unemployment insurance. These scenarios assume two disbursement tranches, each for the second and third quarters. While the Philippines has implemented mechanisms that have a broad coverage of vulnerable families by accounting for the bottom 70% of households (Reyes et al. 2020), we attempt to simulate other policy options for cash transfers to demonstrate the cost-efficiency of these options that may inform policymakers for future similar scenarios.

In the limited scenario, the total allocation for the amelioration is equivalent to PHP 206.7 billion (Reyes et al. 2020), or a disbursement of PHP 5,000 to PHP 8,000 per household to poor families contingent on the families' region of residence. The boosted scenario doubles the total budgetary allocation for amelioration and the disbursement per tranche. This amounts to PHP 413.4 billion. Finally, a broader scenario covers the bottom 60% of households while disbursing PHP 5,000 to PHP 8,000 per household to capture the middle-income families who are vulnerable to fall into poverty. Furthermore, given that unemployed individuals reached at most 7.2 million in 2020 (Philippine Statistics Authority 2020a), we also use the government's scheme on unemployment benefits worth PHP 8,000 per tranche for two tranches during the corresponding quarters of 2020 (Department of Finance 2021). Overall, the third scenario simulates PHP 528.6 billion worth of transfers.

Table 3 summarizes the simulation parameters of the policy scenarios. The general equilibrium effects of transfers, which are reflected in the general equilibrium changes in the labor market variables, are included prior to the imposition of the labor market effects in the microsimulation. Meanwhile, the cash disbursement per covered household enters as non-labor household income after implementing the microsimulation of the changes in the labor market variables.

<TABLE 3 HERE>

V. Results and Discussion

Previous studies and the theoretical model have shown that poverty increases following widespread economic downturns caused by the pandemic. However, there are empirical gaps in terms of tracing the effects of pandemics on welfare through the labor market. Thus, by linking the macroeconomic effects of the pandemic with the Philippine labor market structure, this section presents the empirical evidence that shows the changes in welfare due to the COVID-19 pandemic in all quarters of 2020.

Given the counterfactual scenarios, the CGE results in Table 4 show that the Philippine economy will experience the deepest decline during the second quarter of 2020 should there be no interventions from the government. Exports will be the most affected sector in terms of final demand due to the contraction in domestic production. For the gross sectoral output, agriculture will experience lower contractions relative to the other two macro sector. This reflects the treatment of government lockdown policies on agriculture as an essential sector.

<TABLE 4 HERE>

Apart from the aggregate macroeconomic parameters, the CGE results also show the impact of the pandemic on households. Table 5 shows that at the onset of the pandemic, lower decile groups will experience at least 18% decline in consumption. This is in contrast with a lower decline in higher decline groups amounting to -16% to -17% only. However, during the third and fourth quarters, higher income decile groups will be relatively worse off as seen in at least 11% and 8% decline in the respective quarters. This reflects the compensation to factor endowments of these decile groups, where lower decile groups tend to be endowed more with low-skilled labor.

<TABLE 5 HERE>

In fact, Table 6 shows that in terms of the general equilibrium labor compensation, the wage of low-skilled labor will recover more after the onset of the pandemic than the wage of high-skilled labor. The difference between the second and third quarter simulations for the wage of low-skilled labor amounts to 11.07 percentage points, in contrast with 7.77 percentage point difference for the wage of high-skilled labor.

Table 6 shows that following the fixed labor force assumption of the results, unemployment rates will absorb the labor force dropouts. Hence, during the onset of the pandemic in the second quarter simulation, the general equilibrium unemployment rate will increase from 4.91% in the pre-pandemic scenario to 25.46%. The number of low-skilled labor in the economy and in the macro sectors will decline more than the number of high-skilled labor.

Using the results from Table 6, the CGE is linked to the microsimulation model. Table 7 shows the cumulative effects of the changes in the labor market on the FGT and Gini indices. In the absence of government interventions, poverty headcount will increase from 16.85% during the pre-pandemic scenario to an average of 24.66% for the entirety of 2020. On a year average, this is equivalent to having an additional 8.4 million persons falling below the poverty line in 2020. The main drivers of these increases are the increase in unemployment rate and the decrease in overall wages.

<TABLE 6 HERE>

<TABLE 7 HERE>

The depth of poverty in terms of the poverty gap and the inequality among the poor in terms of poverty severity will also increase on average by about 4 percentage points as seen in Table 7. Furthermore, the second quarter of 2020 will register the highest FGT indices among the four quarters, which highlights the idiosyncratic nature of the pandemic shock on welfare. In fact, poverty headcount will increase by almost 14 percentage points during the onset of the pandemic. This is equivalent to having an additional 14.8 million poor people during the second quarter of 2020.

Since the empirical strategy allows for the simulation of effects of the pandemic on inequality as well, Table 7 shows the trends in the Gini coefficients for all quarters of 2020. The Gini coefficient based on per capita consumption will increase by about 2 percentage points from pre-pandemic levels. The second quarter simulation will also experience the highest increase in Gini coefficient, both in terms of per capita consumption and in terms of individual labor incomes.

Overall, the microsimulation results are ordinally consistent when using the actual observed changes in the labor force, where the deepest welfare decline will happen in the second quarter, followed by the third and fourth quarters (See Appendix B, Table B.6). The increase in the year average poverty headcount to 24.66% provides evidence of a reversal on the previous improvements in poverty headcount by the Philippines from 2015 to 2018, where poverty headcount had declined from 23.5% to 16.7% (Philippine Statistics Authority 2019). Hence, the worsening trends in poverty as well as inequality merit crafting mitigation strategies.

Table 8 shows improvements on the effects of transfers on poverty and inequality in terms of the year-round average of these indicators. A broadened scenario of cash transfers and unemployment insurance will result to the most tempered increase in poverty indicators on average as it covers the bottom 60% of households and disburses unemployment insurance worth PHP 8,000 for two quarters. This indicates that in absolute terms, covering the low- and middle-income households in times of economy-wide shocks such as a pandemic is more effective in tempering the decrease in welfare caused by said shocks than just limiting the assistance given to low-income households.

<TABLE 8 HERE>

While the same trend is observed for the Gini coefficient using per capita consumption as seen in Table 8, inequality among wage workers will increase during the scenarios where amelioration is disbursed. This is due to the general equilibrium effects of transfers on wages, which will increase the gap of wages in absolute terms between low- and high-skilled workers in favor of the latter group (See Appendix B, Tables B.1, B.2, and B.3).

While a broader coverage will temper the increase in poverty greatly in absolute terms, a limited and boosted amelioration will be more cost-efficient. For instance, a limited amelioration will reduce poverty headcount by 1.24% per billion pesos disbursed, and by 1.20% per billion pesos disbursed under a boosted scenario. Thus, this demonstrates a trade-off for the government between a broader coverage of safety nets and choosing the most efficient policy option. The more this trade-off is apparent, the more limited the policy space is for the government.

Overall, the results indicate that there will be reversals in the improvement in poverty headcount on average in the absence of amelioration. Inequality among the population and among wage workers will also increase on a year average. These increases are more pronounced during the simulated onset of the pandemic in the second quarter. Furthermore, while trade-offs exist between efficient amelioration and tempered decrease in welfare in absolute terms, the results indicate that cash transfers will avoid the reversal in poverty gains. These observations are consistent with the conclusion of the theoretical framework of the paper.

VI. Conclusion and Policy Implications

The economic impacts of the COVID-19 pandemic were detrimental especially to the welfare of the most vulnerable. The same was reflected in the Philippines' case. Pre-pandemic economic structures and factor endowments, among others, are pivotal factors in the decreases in welfare. Furthermore, since it has been globally observed that the pandemic has disrupted economic activities of laboring populations, it is expected that the economic impacts of the pandemic and the corresponding policy responses of the government would be transmitted through the labor market. This is illustrated in the theoretical framework and in the empirical strategy.

Using a CGE-microsimulation strategy, we find that for all quarters of 2020 under the pandemic scenario, poverty has increased. The same is true for inequality. In a single year, the pandemic will reverse the country's improvements in poverty headcount if cash transfers to households and affected individuals in the labor force on the average are absent. Meanwhile, on average, poverty and inequality have increased in a year even with the presence of cash transfers, but this increase is tempered whether the cash assistance only covers the poor households or includes the middle-income households. On a quarterly basis, quarters with disbursement may even withstand the decrease in welfare, where poverty rates in these quarters have been below the pre-pandemic levels. However, policymakers face a trade-off between implementing a cost-efficient policy on one hand, and a broad coverage of assistance on the other.

While the paper's main motivation is the COVID-19 pandemic, the results provide important policy implications for future pandemics and other similar exogenous economic shocks. For instance, a reactive approach to combat the welfare effects of such shocks is to increase the government's capacity and liquidity during the shock to disburse transfers to the affected population. Without being limited by the question on the efficiency of a policy, a broad coverage of transfers is effective in mitigating the increases in poverty and worsening inequality. However, to increase the policy space for the government in the face of a trade-off between a cost-efficient and a broader policy option, better targeting mechanisms should be put in place to avoid leakages. Furthermore, labor market cushions such as the provision of unemployment benefits may be effective to temper any declines of welfare due to economy-wide shocks.

A proactive approach to cushion the effects of such shocks is to ensure the robustness of the vulnerable economic sectors. For instance, should similar shocks in the future necessitate the implementation of remote work arrangements, then vulnerable sectors especially under the industry and services macro-sectors must have the capacity to retrofit accordingly. The onset of the pandemic has shown the detrimental effects of the lack of such prior capacities to businesses, which – consistent with our framework – was transmitted to the labor market and finally to households as increases in poverty and inequality. Possible issues within the supply chains, whether local or global, must also be identified and addressed beforehand to secure the various economic sectors from second- and subsequent round effects of such shocks.

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TABLES WITH CAPTIONS

Table 1. Summary of the 2018 Social Accounting Matrix (in billion PHP).

Final Demand			Gross Output	Gross Value Added	Factors	
Consumption	12,279.8	Agriculture	3,416.2	1,717.8	LSk	2,726.2
Investment	6,904.2	Industry	14,967.2	5,460.4	HSk	3,570.9
Government	1,574.6	Services	17,318.1	10,248.9	K	10,583.8
Exports	6,570.5				VAT	546.4
Imports	9,064.0					
TOTAL	18,265.2		35,701.5	17,427.2		17,427.2

Source of basic data: Author’s calculations.
Note: LSk = Low-Skilled Labor, HSk = High-Skilled Labor, K =Capital, VAT = Value Added Tax.
Figures may not add up due to rounding off.

Table 2. Counterfactual Scenarios without Policy Interventions (in proportion of 2020 value added to 2019 levels).

Parameters	2020-Q1	2020-Q2	2020-Q3	2020-Q4
Agriculture change	0.997	1.016	1.012	0.975
Industry change	0.969	0.808	0.913	0.954
Services change	1.001	0.815	0.860	0.896

Source of basic data: Philippine Statistics Authority.

Table 3. Policy Simulation on Cash Transfer for the 2nd and 3rd Quarters.

Simulation	CGE		Microsimulation	
	Disbursement[1]	Coverage	Disbursement[3]	Coverage
Limited scenario	PHP 103.35	Bottom 30%	PHP 5,000 to PHP 8,000	Bottom 30%
Boosted scenario	PHP 206.7	Bottom 30%	PHP 10,000 to PHP 16,000	Bottom 30%
Broadened scenario	PHP 264.3	Bottom 60%	PHP 5,000 to PHP 8,000	Bottom 60%
			PHP 8,000	Unemployed

Note: [1]in billions, divided in 2 tranches per quarter. [2]Disbursement differentiated per region.

Table 4. The 2020 Quarterly General Equilibrium Effects of the Pandemic on the Macroeconomy in the Absence of Mitigating Measures (%).

Macroeconomic Accounts	Q1	Q2	Q3	Q4
Gross Domestic Product (Value Added)	-4.56	-21.37	-15.05	-12.63
Gross Domestic Product (Final Demand)	-1.59	-22.72	-12.67	-10.96
Consumption	-0.37	-17.46	-10.97	-8.18
Investment	-2.96	-21.80	-13.28	-10.56
Government	-1.55	-24.84	1.33	-13.81
Export	-4.53	-33.86	-16.97	-10.61
Import	-3.10	-23.34	-11.51	-7.12
Agricultural Output	-0.82	-10.22	-5.33	-6.65
Industrial Output	-0.69	-22.60	-19.71	-12.44
Service Output	-2.22	-23.95	-13.82	-10.54

Source of basic data: Author’s calculations from the CGE results.

Table 5. The 2020 Quarterly General Equilibrium Effects of the Pandemic on Household Welfare in the Absence of Mitigating Measures (%).

	Q1	Q2	Q3	Q4
Decile 1	-1.60	-18.40	-9.10	-7.40
Decile 2	-1.40	-18.40	-9.30	-7.50
Decile 3	-1.20	-18.30	-9.60	-7.60
Decile 4	-1.10	-18.50	-10.00	-7.90
Decile 5	-0.90	-18.60	-10.40	-8.10
Decile 6	-0.60	-18.10	-10.70	-8.20
Decile 7	-0.50	-18.00	-11.00	-8.30
Decile 8	-0.30	-17.60	-11.30	-8.40
Decile 9	-0.10	-17.40	-11.60	-8.50
Decile 10	0.30	-16.10	-11.60	-8.20

Source of basic data: Author’s calculations from the CGE results.

Note: Welfare is operationalized as changes in household consumption.

Table 6. The 2020 Quarterly General Equilibrium Effects of the Pandemic on the Labor Market in the Absence of Mitigating Measures (%).

	Base	Q1	Q2	Q3	Q4
Unemployment rate	4.91	6.44	25.46	18.90	14.79
Change in Number of High-Skilled Labor	-	-1.40	-21.33	-13.43	-9.58
Change in Agriculture	-	-0.79	-13.11	-7.89	-6.81
Change in Industry	-	1.09	-19.64	-20.26	-10.23
Change in Services	-	-1.82	-21.78	-12.42	-9.53
Change in Number of Low-Skilled Labor	-	-1.71	-21.74	-15.32	-10.77
Change in Agriculture	-	-0.53	-11.51	-7.03	-6.08
Change in Industry	-	-0.99	-20.11	-17.80	-11.91
Change in Services	-	-2.14	-23.46	-15.07	-10.74
Change in Wages	-	-5.31	-23.82	-14.18	-12.63
High-Skilled Labor Wages	-	-4.41	-20.02	-12.25	-11.01
Low-Skilled Labor Wages	-	-6.01	-26.72	-15.65	-13.87

Source of basic data: Author’s calculations from the CGE results.

Table 7. The 2020 Quarterly Microsimulation Effects of the Pandemic on the Welfare in the Absence of Mitigating Measures (%).

	Base	Q1	Q2	Q3	Q4	Year Average
FGT_0: Poverty Headcount	16.85	18.60	30.57	25.79	23.67	24.66
FGT_1: Poverty Gap	3.91	4.60	11.44	8.56	7.26	7.97
FGT_2: Poverty Severity	1.34	1.80	9.06	5.80	4.40	5.27
Gini Coefficient (per capita consumption)	43.72	44.07	46.89	45.75	45.23	45.49
Gini Coefficient (labor income)	35.58	35.83	36.82	36.12	36.03	36.20

Source of basic data: Author's calculations from the microsimulation results.
Note: Microsimulation is implemented with 30 iterations using the 2018 FIES-LFS. Results indicate the mean of these iterations, with a 95% level of confidence. Appendix B, Tables B.4 and B.5 detail the cumulative effects of the labor market changes per quarter. Pre-pandemic baseline parameters are from the microsimulation as well.

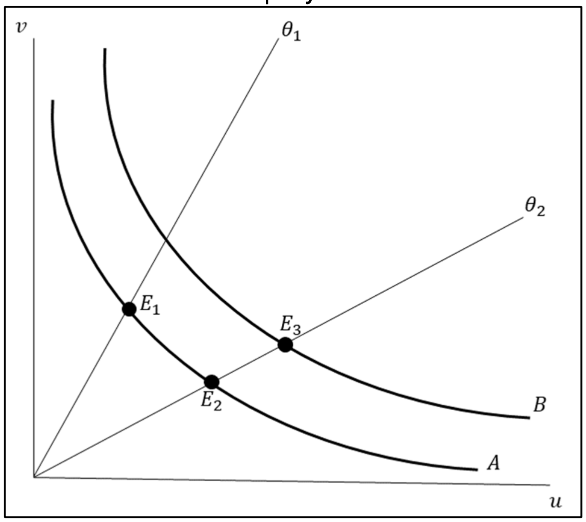
Table 8. Average Welfare Indicators for 2020 under COVID-19 under Different Amelioration Scenarios (%).

	No Assistance	Limited	Boosted	Broadened
FGT_0: Poverty Headcount	24.66	22.10	19.70	18.83
FGT_1: Poverty Gap	7.97	6.35	5.27	4.98
FGT_2: Poverty Severity	5.27	4.03	3.30	3.04
Gini Coefficient (per capita consumption)	45.49	44.43	43.56	43.20
Gini Coefficient (labor income)	36.20	36.35	36.49	37.71
Percentage point reduction in poverty headcount per billion PHP disbursed	-	1.24	1.20	1.11

Source of basic data: Author's calculations from the microsimulation results.
Note: Indicators are taken from the average of four quarters of simulations. See Appendix B, Table B.5 for the simulation results with standard deviations.

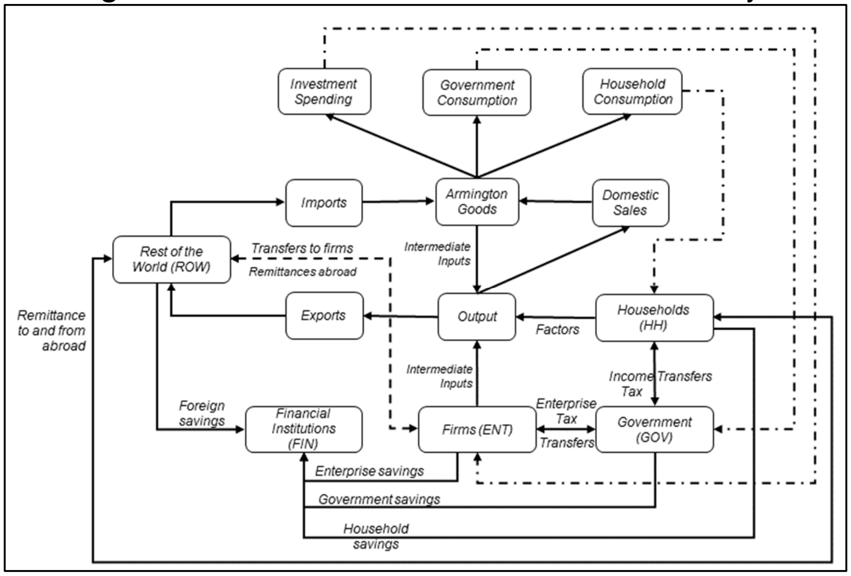
FIGURES AND FIGURE CAPTIONS

Figure 1. The Effect of a Negative Economic Shock on Vacancies and Unemployment.



Source: Pissarides (1985; 2000).

Figure 2. The Flow of Transactions in the Economy.



Source: Modification from Markusen and Rutherford (2004).

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Disclosure statement

The authors report there are no competing interests to declare.

Data availability statement

The data that support the findings of this study are openly available in the Philippine Statistics Authority's website. The microdata used in the microsimulation can be requested from the same government agency.

The Welfare Impact of the COVID-19 Pandemic: An Analysis of the Philippine Labor Market using the CGE-Microsimulation Approach

Appendix A. Annex to the Theoretical Framework

The model we develop in the theoretical framework establishes that labor supply and labor demand are linked through a matching function due to labor market imperfections. With this, it has been further shown that as shocks on aggregate economic output through changes in productivity occur, this will be partly absorbed by real wages on one hand, and by unemployment on the other hand.

This appendix section serves as an accompaniment of the theoretical framework that provides the solutions to the critical parts of the theoretical framework. Mainly, the annex outlines the following: the Nash bargaining wage determination derivation of the job creation and job destruction, the dynamics of job creation and job destruction due to a proportional productivity shock and due to changes in nonmarket activities, and the effects of these changes on poverty rate. The solutions and derivations in this section are lifted from Pissarides (2000).

As a prerequisite, the model hinges on the assumption that there are imperfections in the labor market; hence, the matching technologies in the labor market with a fixed labor force L, unemployment rate u, and vacancy rate v at a specific time period can be represented by,

$$mL = m(uL, vL) \tag{A.1.}$$

From Equation (A.1), the rate of filling up vacancies is given by $q(\theta) = m\left(\frac{u}{v} = \theta, 1\right)$, where $q(\theta)$ is a decreasing function of the vacancy-unemployed ratio θ, the market tightness indicator. With this, the flow from unemployment to employment is given by $\frac{mL}{uL}$ or in vacancy-unemployment terms, $\theta q(\theta)$. Equation (A.1) is operant in the change in unemployment rate as specified in Equation (1), as well as in the entirety of the theoretical framework.

A. Nash bargaining wage determination

While both firms and workers optimize their returns in job matches, the economic rent or surplus generated from a realized job match must be shared by these two entities. For the firms' perspective, let each individual firm have a discounted expected profit from occupied jobs $J(x)$ and a discounted expected profit from vacancies V. Therefore, the asset value of occupied jobs with productivity that falls within the range of $R \leq x \leq 1$ is given by,

$$\underbrace{rJ(x)}_{\substack{\text{asset value} \\ \text{of occupancy}}} = \underbrace{px}_{\substack{\text{output} \times \\ \text{idiosyncratic} \\ \text{productivity}}} - \underbrace{w(x)}_{\substack{\text{cost of} \\ \text{labor or} \\ \text{wages}}} + \lambda \int_R^1 J(s)dG(s) - \lambda J(x) \tag{A.2.}$$

Classification: GENERAL

Equation (A.2) shows that the asset value of occupied jobs is determined by the net return from the job match $\left(px - w(x)\right)$, and the difference in initial and new expected profits after a shock.

For the decision to open jobs, firms create jobs with an expectation of full productivity, that is, $x = 1$. Therefore, the asset value of a vacancy is given by,

$$rV = -pc + q(\theta)[J(1) - V] \qquad \text{(A.3.)}$$

Equation (A.3) shows that firms' expected profit from vacancies are penalized by a hiring cost given by the value of the fixed cost for all produced output. Furthermore, at steady-state, firms exhaust all positive profits from vacancies. Therefore, at steady-state, then the job creation must occur with the condition that,

$$\underbrace{J(1)}_{\substack{expected\ profit \\ from\ occupancy}} = \frac{pc}{\underbrace{q(\theta)}_{\substack{expected\ cost\ of \\ hiring}}} \qquad \text{(A.4.)}$$

The asset value of being employed and unemployed for workers follow the same specification as in Equations (A.2) and (A.3). Therefore, the asset value of being employed is given by,

$$rW(x) = w(x) + \lambda \int_R^1 W(s)dG(s) + \lambda G(R)U - \lambda W(x) \qquad \text{(A.5.)}$$

While unemployment gives an asset value of,

$$rU = b + \theta q(\theta)[W(x) - U] \qquad \text{(A.6.)}$$

Similar to Equation (A.2), the asset value of employment is dependent on idiosyncratic productivity. Furthermore, the asset value of unemployment stems from the assumption that there are nonmarket returns from unemployment, i.e., unemployment benefits.

Equations (A.2), (A.3), (A.5), and (A.6) serve as the foundations of the market behavior of firms and workers. Without any loss of generality, let there be no idiosyncratic effects on productivity; thus, $x = 1$. Then, by getting the first-order condition of Equation (2), it satisfies the equation below,

$$W - U = \beta[J + W - V - U] \qquad \text{(A.7.)}$$

which clearly shows that β is the worker's share of the total surplus generated from a match.

However, if J and W from Equations (A.2) and (A.5) are substituted into Equation (A.7), and noting that the expected profit from job vacancies is fully exhausted in equilibrium, $V = 0$, then Equation (A.7) can be converted into,

$$w = rU + \beta(p \cdot 1 - rU) \quad \text{(A.8.)}$$

where Equation (A.8) interprets the wage of workers as a sum of their reservation wage and a fraction β of the net surplus from the job match. Moreover, Equation (A.8) shows that should there be no idiosyncratic effects on productivity, all jobs will be renumerated with the same wage rates. A more generalized version of this is $w(x) = rU + \beta(px - rU)$.

Holding the assumption that there are no idiosyncratic effects on productivity, $x = 1$, then using the equilibrium condition $J(1) = \frac{pc}{q(\theta)}$ as shown in Equation (A.4) and Equation (A.8) to substitute $W - U$ from Equation (A.6) yields,

$$rU = b + \frac{\beta}{1-\beta} pc\theta \quad \text{(A.9.)}$$

which generates Equation (A.10) below when rU in Equation (A.9) is substituted into Equation (A.8),

$$w = (1-\beta)b + \beta(p \cdot 1 + c\theta) \quad \text{(A.10.)}$$

By relaxing the assumption that there are no idiosyncratic productivities, then Equation (A.10) becomes Equation (3).

B. Job creation and job destruction

Because of the existence of idiosyncratic productivity—and as a corollary, reservation productivity—a simple relation between job creation and wages (which stand for labor demand and labor supply, respectively) is not sufficient to demonstrate the comparative statics that are operant in the labor market. This is because with the introduction of idiosyncratic productivity, job destruction becomes endogenous to the model. Therefore, we derive the job creation and job destruction relations that are described by the relationship between reservation productivity R and market tightness or vacancy-unemployment ratio θ.

By substituting the wage equation from Equation (3) into the expected profit of job occupancies as described in Equation (A.2), this results to Equation (A.11),

$$(r+\lambda)J(x) = (1-\beta)(px - b) - \beta pc\theta + \lambda \int_R^1 J(s)dG(s) \quad \text{(A.11.)}$$

Then, by letting idiosyncratic productivities be equal to reservation productivities, which implies that expected profits of job occupancies under reservation productivity will be equal to the fully exhausted expected profits of a vacancy $J(R) = V = 0$, then,

$$(r+\lambda)J(x) = (1-\beta)(pR - b) - \beta pc\theta + \lambda \int_R^1 J(s)dG(s) \quad \text{(A.11.')}$$

With this, subtracting Equation (A.11') from (A.11) yields,

$$(r+\lambda)J(x) = (1-\beta)p(x - R) \quad \text{(A.12.)}$$

To get the job creation condition, let $x = 1$ in Equation (A.12). As established in the framework, if $J(1) = \frac{pc}{q(\theta)}$, then the job creation condition is given by the equation below,

$$\frac{(r+\lambda)pc}{q(\theta)} = (1-\beta)p(1-R) \qquad \text{(A.13.)}$$

The job creation condition is downward sloping in the θ-R space since if there is a higher reservation productivity, then the life span of a job tends to be shorter. This becomes a disincentive to open more vacancies, which leads to the loosening of the labor market or a decline in θ.

Meanwhile, to get the job destruction condition, let $J(x) = \frac{(1-\beta)p(x-R)}{r+\lambda}$ with from Equation (A.15) be substituted into Equation (A.11'). This yields the equation below:

$$(r+\lambda)J(x) = (1-\beta)(pR-b) - \beta pc\theta + \frac{\lambda(1-\beta)p}{r+\lambda}\int_R^1 (s-R)dG(s) \qquad \text{(A.14.)}$$

Following this, let idiosyncratic productivity by equal to reservation productivity, thus $J(R) = V = 0$, then this gives,

$$0 = (1-\beta)(pR-b) - \beta pc\theta + \frac{\lambda(1-\beta)p}{r+\lambda}\int_R^1 (s-R)dG(s) \qquad \text{(A.15.)}$$

Equation (A.15) is the job destruction condition, where it suggests that should market tightness increase, opportunities tend to be better, and wages tend to be higher. Therefore, jobs with lower productivity are destroyed, leading to an increase in reservation productivity.

C. Comparative statics from shocks

The previous section has described the derivation of the job creation and destruction conditions as in Equations (A.13) and (A.15). This section uses these equations to describe the comparative statics from two types of shocks, namely, a proportional change in productivity p and a change in returns from nonmarket activities b. Since the equilibrium of job creation and job destruction is found at a unique point (θ^*, R^*), then the aim of these comparative statics is to describe the change in this equilibrium point.

For a proportional change in productivity, let Equation (A.13) be differentiated with respect to p, which yields the following,

$$-\frac{1-\beta}{r+\lambda}\frac{\partial R}{\partial p} = \frac{c\eta(\theta)}{\theta q(\theta)}\frac{\partial \theta}{\partial p} \qquad \text{(A.16.)}$$

where Equation (A.16) uses the elasticity notation, $\eta(\theta) = -\frac{\partial q(\theta)}{\partial \theta}\frac{\theta}{q(\theta)}$ and it lies strictly within the range of $0 \leq \eta(\theta) \leq 1$. Moreover, let Equation (A.15) be differentiated with respect to p, yielding,

$$\frac{\partial R}{\partial p} + \frac{b}{p^2} - \frac{\beta c}{1-\beta}\frac{\partial \theta}{\partial p} + \frac{\lambda}{r+\lambda}[1 - G(R)]\frac{\partial R}{\partial p} = 0 \quad \text{(A.17.)}$$

Substituting $\frac{\partial R}{\partial p}$ in Equation (A.17) into (A.16) shows that the sign of $\frac{\partial \theta}{\partial p}$ is given by the following equation,

$$\frac{\partial \theta}{\partial p} = \frac{b(1-\beta)\theta q(\theta)}{cp^2[\eta(r+2\lambda)[1-G(R)] + \beta\theta q(\theta)]} > 0 \quad \text{(A.18.)}$$

Equation (A.18) shows that market tightness changes directly with respect to any proportional change in productivity. Thus, in instances where a negative economic shock occurs, market tightness loosens or goes down as well.

Meanwhile, substituting $\frac{\partial \theta}{\partial p}$ in Equation (A.17) into (A.16) shows that the sign of $\frac{\partial R}{\partial p}$ is given by the following equation,

$$\frac{\partial R}{\partial p} = -\frac{\beta b \eta c^2 (r+\lambda)}{p^2\{(1-\beta)^2\theta q(\theta) + \beta\eta c^2(r+2\lambda)[1-G(R)]\}} < 0 \quad \text{(A.19.)}$$

which shows that reservation productivity increases should a proportional decrease in overall productivity occur.

Using these results and Equation (1'), a change in unemployment rate will be inversely proportional to a change in productivity,

$$\frac{\partial u}{\partial p} = \frac{[\lambda G(R) + \theta q(\theta)]\frac{\partial R}{\partial p} - \lambda G(R)\left[\lambda\frac{\partial R}{\partial p} + \theta\frac{\partial q}{\partial \theta}\frac{\partial \theta}{\partial p} + q(\theta)\frac{\partial \theta}{\partial p}\right]}{[\lambda G(R) + \theta q(\theta)]^2} < 0 \quad \text{(A.20.)}$$

and a change in wage will always follow the direction of a change in productivity as described in Equation (4).

Apart from a change in productivity, the change in returns from nonmarket activities must also be captured since the research problem investigates the effects of cash transfers on welfare. In this study, nonmarket returns are operationalized as payments to unemployed individuals, which makes nonmarket returns operationalized as non-labor market returns. To do this, let Equation (A.13) be differentiated with respect to b, which yields the following,

$$-\frac{1-\beta}{r+\lambda}\frac{\partial R}{\partial b} = \frac{c\eta(\theta)}{\theta q(\theta)}\frac{\partial \theta}{\partial b} \quad \text{(A.21.)}$$

Moreover, let Equation (A.15) be differentiated with respect to b, yielding,

$$\frac{\partial R}{\partial b} - \frac{1}{p} - \frac{\beta c}{1-\beta}\frac{\partial \theta}{\partial b} + \frac{\lambda}{r+\lambda}[1-G(R)]\frac{\partial R}{\partial b} = 0 \qquad \text{(A.22.)}$$

From Equations (A.21) and (A.22), the same procedure as with the change in productivity can be done. Thus, for the change in market tightness, there is an inverse relationship between market tightness and nonmarket returns:

$$\frac{\partial \theta}{\partial b} = -\frac{\theta q(\theta)}{pc[\eta(r+2\lambda)[1-G(R)] + \beta\theta q(\theta)]}(1-\beta) < 0 \qquad \text{(A.23.)}$$

Meanwhile, for the change in reservation productivity, Equation (A.23) shows that reservation productivity is directly proportional with a change in nonmarket returns,

$$\frac{\partial R}{\partial b} = \frac{\beta\eta c^2(r+\lambda)}{p\{(1-\beta)^2\theta q(\theta) + \beta\eta c^2(r+2\lambda)[1-G(R)]\}} > 0 \qquad \text{(A.24.)}$$

These results are clearly the case since an increase in nonmarket returns will shift the job destruction curve upward and to the left in the θ-R space, while the job creation curve remains. Therefore, at this increase in nonmarket returns, equilibrium market tightness goes down while equilibrium reservation productivity goes up.

Extending the analysis into unemployment rate and using the same formulation in Equation (A.20), unemployment rate will increase given the increase in nonmarket returns. Finally, wages will also increase amidst an increase in nonmarket returns.

$$\frac{\partial E[w(x) \mid x \geq R]}{\partial b} = (1-\beta) + \beta pc\frac{\partial \theta}{\partial b} > 0 \qquad \text{(A.25.)}$$

This increase will occur since the loosening of the labor market has a lesser absolute value effect than the fixed bargaining strength of the firm $(1-\beta)$. This is evident when contrasting $(1-\beta)$ and the second term in Equation (A.25), and how the second term is $\frac{\beta pc\frac{\partial \theta}{\partial b}}{(1-\beta)}$ less than $(1-\beta)$ when using Equation (A.23).

D. Comparative statics in poverty rate

We outline in the theoretical framework that poverty increases given a proportional decrease in productivity through the change brought by the latter on the income-to-needs ratio. This section extends the analyses by analyzing the change in poverty as brought about by a change in general productivity and in nonmarket returns.

Specifically, poverty increases with a decrease in general productivity due to the effects of productivity change on the income-to-needs ratio. This arises from the fact that when Equation (5) is differentiated with respect to general productivity, the income-to-needs ratio change in the same direction as general productivity as seen below,

$$\frac{\partial E[I^*]}{\partial p} = \frac{1}{T} \times \left\{ \frac{\partial E[w(x) \mid x \geq R]}{\partial p} \right\} > 0 \quad \text{(A.26.)}$$

Then, following Gottschalk and Danziger (1985), we assume that μ and σ are expressed in terms of the mean and variance of I^*,

$$\mu = \ln\left\{ \frac{(\alpha + k)^2}{[\delta^2 + (\alpha + k)^2]^{\frac{1}{2}}} \right\} \qquad \sigma^2 = \ln\left\{ \frac{[\delta^2 + (\alpha + k)^2]}{(\alpha + k)^2} \right\} \quad \text{(A.27.)}$$

where $\alpha = E[I^*]$ and $\delta^2 = Var[I^*]$. Thus, upon totally differentiating the theoretical poverty measure in Equations (6) or (8), the partial derivative of poverty with respect to the expected income-to-needs ratio is given by,

$$\frac{\partial P}{\partial E[I^*]} = \frac{\phi(h)}{\sigma^2(\alpha + k)[\delta^2 + (\alpha + k)^2]} \times \{h\delta^2 - \sigma[2\delta^2 + (\alpha + k)^2]\} < 0 \quad \text{(A.28.)}$$

where $h\delta^2 < 2\sigma\delta^2 + \sigma(\alpha + k)^2$.

Finally, holding all things constant, and using the income-to-needs ratio definition, it is easy to see that the income-to-needs ratio is expected to increase given an increase in nonmarket returns,

$$\frac{\partial E[I^*]}{\partial b} = \frac{1}{T} \times \left\{ \frac{\partial E[w(x) \mid x \geq R]}{\partial b} + 1 \right\} > 0 \quad \text{(A.29.)}$$

However, should a change in productivity occur prior to a change in nonmarket returns, then the income-to-needs ratio still changes in the same direction as the change in general productivity, but at a decreasing rate. This is shown by differentiating Equation (5) with the level of productivity and the nonmarket income variable,

$$\begin{aligned} \frac{\partial}{\partial b}\left(\frac{\partial E[I^*]}{\partial p}\right) &= \frac{p\beta(1-\beta)}{T[\eta(r + 2\lambda[1 - G(R)] + \beta\theta q(\theta)]^2} \\ &\quad \times \Big\{ \big[\eta(r + 2\lambda)\big(1 - G(R)\big) + \beta\theta q(\theta)\big][b\gamma + \theta q(\theta)] \\ &\quad - b\theta q(\theta)\left[\beta\gamma - \eta(r + 2\lambda)\frac{\partial R}{\partial b}\right]\Big\} + \beta c\frac{\partial \theta}{\partial b} < 0 \end{aligned} \quad \text{(A.30.)}$$

where $\gamma = \frac{\partial \theta}{\partial b}[-\eta(\theta) + 1] \leq 0$. This clearly shows that the decrease in income-to-needs ratio (and therefore poverty) following a decrease in general productivity might be tempered by an increase in nonmarket returns.

Appendix B. Simulation Results for the CGE-Microsimulation Implementation.

Table B.1. The 2020 Quarterly General Equilibrium Effects of the Pandemic on the Labor Market with Limited Amelioration (%).

	Q1	Q2	Q3	Q4
Gross Domestic Product (Factor Income)	-4.56	-21.39	-15.07	-12.66
Gross Domestic Product (Final Demand)	-1.59	-22.69	-12.65	-10.96
Unemployment rate	6.44	25.40	18.84	14.79
Change in Number of High-Skilled Labor	-1.40	-21.64	-13.80	-9.58
Agriculture	-0.79	-10.78	-5.72	-6.81
Industry	1.09	-18.97	-19.42	-10.23
Services	-1.82	-22.31	-13.04	-9.53
Change in Number of Low-Skilled Labor	-1.71	-21.50	-15.05	-10.77
Agriculture	-0.53	-8.42	-4.14	-6.08
Industry	-0.99	-20.20	-17.81	-11.91
Services	-2.14	-23.36	-14.94	-10.74
Change in Wages	-5.31	-24.26	-14.76	-12.65
High-Skilled	-4.41	-19.67	-11.90	-11.04
Low-Skilled	-6.01	-27.76	-16.94	-13.89

Source of basic data: Author’s calculations from the CGE results.

Table B.2. The 2020 Quarterly General Equilibrium Effects of the Pandemic on the Labor Market with Boosted Amelioration (%).

	Q1	Q2	Q3	Q4
Gross Domestic Product (Factor Income)	-4.56	-21.41	-15.09	-11.20
Gross Domestic Product (Final Demand)	-1.59	-22.66	-12.64	-10.96
Unemployment rate	6.44	25.34	18.78	14.79
Change in Number of High-Skilled Labor	-1.40	-21.95	-14.17	-9.58
Agriculture	-0.79	-8.46	-3.58	-6.81
Industry	1.09	-18.31	-18.59	-10.23
Services	-1.82	-22.83	-13.66	-9.53
Change in Number of Low-Skilled Labor	-1.71	-21.27	-14.78	-10.77
Agriculture	-0.53	-5.34	-1.29	-6.08
Industry	-0.99	-20.30	-17.82	-11.91
Services	-2.14	-23.26	-14.81	-10.74
Change in Wages	-5.31	-24.69	-15.33	-11.20
High-Skilled	-4.41	-19.33	-11.55	-9.55
Low-Skilled	-6.01	-28.79	-18.21	-12.46

Source of basic data: Author’s calculations from the CGE results.

Table B.3. The 2020 Quarterly General Equilibrium Effects of the Pandemic on the Labor Market with Broadened Amelioration (%).

	Q1	Q2	Q3	Q4
Gross Domestic Product (Factor Income)	-4.56	-21.41	-15.08	-12.68
Gross Domestic Product (Final Demand)	-1.59	-22.68	-12.67	-10.96
Unemployment rate	6.44	25.24	18.66	14.79
Change in Number of High-Skilled Labor	-1.40	-21.75	-13.96	-9.58
Agriculture	-0.79	-9.09	-4.18	-6.81
Industry	1.09	-18.72	-18.96	-10.23
Services	-1.82	-22.51	-13.34	-9.53
Change in Number of Low-Skilled Labor	-1.71	-21.20	-14.69	-10.77
Agriculture	-0.53	-6.17	-2.07	-6.08
Industry	-0.99	-20.54	-18.06	-11.91
Services	-2.14	-22.97	-14.50	-10.74
Change in Wages	-5.31	-24.62	-15.25	-12.68
High-Skilled	-4.41	-19.46	-11.68	-11.06
Low-Skilled	-6.01	-28.56	-17.97	-13.91

Source of basic data: Author’s calculations from the CGE results.

Table B.4. The 2020 Cumulative Welfare Effects of the Pandemic caused by the Changes in the Labor Market without Amelioration (FGT in %).

	Q1	Q2	Q3	Q4
FGT_0: Poverty Headcount				
Baseline	16.85	16.85	16.85	16.85
Unemployment	17.52	26.45	23.24	21.29
Sector of Employment	17.52	26.45	23.24	21.29
Occupational Category	17.52	26.45	23.24	21.29
Wage Structure	17.67	26.95	23.51	21.53
Aggregate Wage Level	18.61	30.59	25.84	23.70
Skill Composition	18.60	30.57	25.79	23.67
FGT_1: Poverty Gap				
Baseline	3.91	3.91	3.91	3.91
Unemployment	4.26	9.53	7.53	6.36
Sector of Employment	4.26	9.53	7.53	6.36
Occupational Category	4.26	9.53	7.53	6.36
Wage Structure	4.30	9.74	7.63	6.44
Aggregate Wage Level	4.60	11.45	8.57	7.27
Skill Composition	4.60	11.44	8.56	7.26
FGT_2: Poverty Severity				
Baseline	1.34	1.34	1.34	1.34
Unemployment	1.65	7.52	5.11	3.86
Sector of Employment	1.65	7.52	5.11	3.86
Occupational Category	1.65	7.52	5.11	3.86
Wage Structure	1.67	7.62	5.15	3.90
Aggregate Wage Level	1.80	9.06	5.80	4.40
Skill Composition	1.80	9.06	5.80	4.40
Gini Coefficient (per capita consumption)				
Baseline	0.4372	0.4372	0.4372	0.4372
Unemployment	0.4389	0.4612	0.4534	0.4485
Sector of Employment	0.4389	0.4612	0.4534	0.4485
Occupational Category	0.4389	0.4612	0.4534	0.4485
Wage Structure	0.4398	0.4646	0.4552	0.4501
Aggregate Wage Level	0.4407	0.4689	0.4577	0.4524
Skill Composition	0.4407	0.4689	0.4575	0.4523
Gini Coefficient (labor income)				
Baseline	0.3558	0.3558	0.3558	0.3558
Unemployment	0.3557	0.3548	0.3551	0.3554
Sector of Employment	0.3557	0.3548	0.3552	0.3554
Occupational Category	0.3557	0.3548	0.3552	0.3554
Wage Structure	0.3583	0.3684	0.3612	0.3604
Aggregate Wage Level	0.3582	0.3681	0.3609	0.3602
Skill Composition	0.3583	0.3682	0.3612	0.3603

Source of basic data: Author’s calculations from microsimulation results.

Table B.5. The 2020 Welfare Effects of the Pandemic with and without Amelioration at 95% Confidence, n = 30 (FGT in %, standard errors in parentheses).

	Q1	Q2	Q3	Q4
FGT_0: Poverty Headcount				
No Disbursement	18.59996 (0.0054514)	30.57497 (0.0141646)	25.78827 (0.0118823)	23.66735 (0.0102651)
Limited	18.59996 (0.0054514)	25.53108 (0.016585)	20.58033 (0.0123889)	23.67047 (0.0102582)
Boosted	18.59996 (0.0054514)	20.70937 (0.0165869)	16.07419 (0.0143977)	23.40732 (0.0102071)
Broadened	18.59996 (0.0054514)	17.83047 (0.0121138)	15.21546 (0.0088496)	23.67455 (0.0103082)
FGT_1: Poverty Gap				
No Disbursement	4.59819 (0.0027281)	11.44248 (0.0117073)	8.561083 (0.00708)	7.261826 (0.0067273)
Limited	4.59819 (0.0027281)	7.913521 (0.0106556)	5.642043 (0.0069518)	7.263669 (0.0067273)
Boosted	4.59819 (0.0027281)	5.5372 (0.0095674)	3.781916 (0.0067457)	7.155594 (0.0067293)
Broadened	4.59819 (0.0027281)	4.524752 (0.0066345)	3.53611 (0.0059091)	7.26553 (0.0067273)
FGT_2: Poverty Severity				
No Disbursement	1.801935 (0.0194026)	9.064113 (0.1422301)	5.803176 (0.0779639)	4.404574 (0.0560727)
Limited	1.801935 (0.0194026)	6.171267 (0.1388847)	3.749599 (0.0758195)	4.405781 (0.056079)
Boosted	1.801935 (0.0194026)	4.459126 (0.1262371)	2.600891 (0.0720814)	4.335846 (0.0557161)
Broadened	1.801935 (0.0194026)	3.631238 (0.1178039)	2.31301 (0.0663564)	4.406999 (0.0560853)
Gini Coefficient (per capita consumption)				
No Disbursement	0.4406952 (0.0000221)	0.468891 (0.0000852)	0.4575461 (0.0000588)	0.4522837 (0.0000592)
Limited	0.4406952 (0.0000221)	0.4471945 (0.0000879)	0.4370785 (0.0000542)	0.4522898 (0.0000592)
Boosted	0.4406952 (0.0000221)	0.4292553 (0.0000804)	0.4203592 (0.0000562)	0.451962 (0.0000596)
Broadened	0.4406952 (0.0000221)	0.4189 (0.0000605)	0.4160629 (0.0000486)	0.4522949 (0.0000593)
Gini Coefficient (labor income)				
No Disbursement	0.3582754 (0.0000343)	0.3681507 (0.0001915)	0.3612216 (0.0001556)	0.3603421 (0.000143)
Limited	0.3582754	0.3710723	0.3641517	0.3603417

	(0.0000343)	(0.0001945)	(0.0001516)	(0.000143)
Boosted	0.3582754	0.3740161	0.3671291	0.3603665
	(0.0000343)	(0.0002003)	(0.0001465)	(0.000143)
Broadened	0.3582754	0.3895976	0.4000063	0.3603413
	(0.0000343)	(0.0001615)	(0.0001269)	(0.000143)

Source of basic data: Author's calculations from microsimulation results.

Table B.6. Comparison of the Cumulative Microsimulation Results using the General Equilibrium Labor Market Simulations and Actual Labor Market Changes for 2020 (in %).

	Q2		Q3		Q4	
	GE	LFS	GE	LFS	GE	LFS
FGT_0: Poverty Headcount						
Baseline	16.85	16.85	16.85	16.85	16.85	16.85
Unemployment	26.45	29.60	23.24	21.78	21.29	22.16
Sector of Employment	26.45	29.60	23.24	21.78	21.29	22.16
Occupational Category	26.45	29.60	23.24	21.78	21.29	22.16
Wage Structure	26.95	31.41	23.51	21.76	21.53	21.76
Aggregate Wage Level	30.59	38.26	25.84	22.75	23.70	22.14
Skill Composition	30.57	38.09	25.79	22.75	23.67	21.98
FGT_1: Poverty Gap						
Baseline	3.91	3.91	3.91	3.91	3.91	3.91
Unemployment	9.53	11.61	7.53	6.67	6.36	6.89
Sector of Employment	9.53	11.61	7.53	6.67	6.36	6.89
Occupational Category	9.53	11.61	7.53	6.67	6.36	6.89
Wage Structure	9.74	12.50	7.63	6.65	6.44	6.74
Aggregate Wage Level	11.45	16.83	8.57	7.03	7.27	6.87
Skill Composition	11.44	16.74	8.56	7.02	7.26	6.84
FGT_2: Poverty Severity						
Baseline	1.34	1.34	1.34	1.34	1.34	1.34
Unemployment	7.52	10.01	5.11	4.04	3.86	4.21
Sector of Employment	7.52	10.01	5.11	4.04	3.86	4.21
Occupational Category	7.52	10.01	5.11	4.04	3.86	4.21
Wage Structure	7.62	10.50	5.15	4.04	3.90	4.14
Aggregate Wage Level	9.06	15.51	5.80	4.26	4.40	4.22
Skill Composition	9.06	15.45	5.80	4.26	4.40	4.21
Gini Coefficient (per capita consumption)						
Baseline	43.72	43.72	43.72	43.72	43.72	43.72
Unemployment	46.12	46.94	45.34	45.03	44.85	45.13
Sector of Employment	46.12	46.94	45.34	45.03	44.85	45.13
Occupational Category	46.12	46.94	45.34	45.03	44.85	45.13
Wage Structure	46.46	48.14	45.52	45.00	45.01	44.84
Aggregate Wage Level	46.89	48.96	45.77	45.10	45.24	44.87
Skill Composition	46.89	48.91	45.75	45.10	45.23	44.84
Gini Coefficient (labor income)						
Baseline	35.58	35.58	35.58	35.58	35.58	35.58
Unemployment	35.48	35.41	35.51	35.54	35.54	35.54
Sector of Employment	35.48	35.41	35.52	35.54	35.54	35.54
Occupational Category	35.48	35.41	35.52	35.54	35.54	35.54
Wage Structure	36.84	41.41	36.12	35.46	36.04	34.63
Aggregate Wage Level	36.81	41.76	36.09	35.44	36.02	34.62

Skill Composition	36.82	48.91	36.12	35.44	36.03	34.80

Note: GE = Microsimulation using the general equilibrium labor market effects; LFS = Microsimulation using the actual observed changes from the 2019 and 2020 Labor Force Surveys.

Source of basic data: Author’s calculations from CGE results; Philippine Statistics Authority.