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The COVID-19 pandemic has affected Indonesia severely. It was initially

an urban event, but the loss of urban jobs has induced a large urban to rural

migration, which we call de-urbanisation. This phenomenon temporarily

reversed the long-term process of rural to urban reallocation of labour. In

early 2021 the approximate size of this de-urbanisation was known, but not

its effects. This paper analyses the general equilibrium consequences of this

overlooked feature of the pandemic. The analysis shows that taking de-

urbanisation into account, the negative economic impact of the pandemic is

largest among rural, not urban households, especially the poorest.

Key words: De-industrialisation; Indonesia; COVID-19; structural change; rural poverty;

urban poverty; inequality.

JEL codes: I15; O12; O53.

Pandemic-induced De-urbanisation in Indonesia

Peter Warr and Arief Anshory Yusuf

1. Introduction

In early 2021, after roughly one year of the ongoing Covid-19 pandemic, Indonesia was severely affected in both health and economic terms. Well over one million people had been infected by the virus, out of a total population of 270 million. More than 31,000 deaths were confirmed, and many additional unconfirmed deaths probably occurred. The hospital system was overloaded and close to collapse. The economic recession induced by the pandemic was by far the most severe since the Asian Financial Crisis just over two decades before. Data recently released showed that between August 2019 and August 2020 Indonesia's real GDP contracted by 3.5 per cent, which can be compared with the pre-pandemic expectation of roughly 5 per cent growth. Relative to that base, the contraction in GDP during 2020 was at least 8 per cent.

In health terms, the pandemic affected urban areas the most. Urban infection rates were far higher than rural rates. In addition, the economic sectors suffering the greatest contraction were those most concentrated in urban areas – manufacturing and some services. The urban economic contraction was not primarily caused directly by infections but by the shutdowns, restrictions on mobility and social distancing that the authorities understandably implemented in an effort to contain the spread of infection (Hill 2021). These policy responses mainly impacted urban areas. Nevertheless, the response of urban households to the economic contraction they experienced clearly did affect rural households. Millions of urban workers and their families relocated from urban areas to rural villages, partly to escape the danger of the pandemic itself, but more particularly in response to the loss of their jobs, hoping to find whatever employment was available and at least to obtain food. To date, this

aspect of the pandemic has been neglected. Its general equilibrium impact, including its effects on urban and rural households, is the subject of this paper.

The urban to rural migration – de-urbanisation – that occurred during 2020 was a reversal of the process of urbanisation that had accompanied half a century of growth-induced structural transformation of the Indonesian economy. Over five decades, steady urbanisation had occurred in combination with the relative decline of agriculture and the expansion of manufacturing and services (Timmer 2014). Data from the government's Labour Force Survey indicate that in 1971 agriculture employed 66 per cent of the total Indonesian workforce. In 2019 that proportion was 12 per cent. Through the decade of the 2010s total agricultural employment had declined at an average annual rate of about one million workers, or 2.5 per cent of the agricultural workforce.

The pandemic reversed that process, at least temporarily. Over the year from August 2019 to August 2020, non-agricultural employment contracted by 3.1 million, as the tight programme of lockdowns and social distancing decimated urban jobs. Agricultural employment actually increased by 2.8 million, fully 7.8 per cent of the 2020 agricultural workforce of 35.9 million and 2 per cent of the total workforce of 138.2 million. Natural increase over the year added a further 2.4 million to the total workforce. Nevertheless, overt unemployment increased by only 2.7 million. These magnitudes mean that the new entrants to the workforce plus the urban workers losing their jobs summed to 5.5 million. Of these, 2.8 million, just over half, joined the existing agricultural workforce and the other 2.7 million became unemployed. Half of the pool of urban workers losing their jobs plus the new entrants could not afford to remain unemployed within urban areas, where the immediate prospects were so bleak and public unemployment assistance is non-existent. For many, their movement to the countryside was a return to the regions from which they or their parents had migrated in recent decades. De-urbanisation was an adaptive response to the pandemic.

We wish to analyse the effects that the de-urbanisation described above has on the structure of the Indonesian economy and also its effects on rural and urban households, including effects on poverty incidence and inequality. Structural effects will depend on changes in industry costs and product prices. Effects on poverty will depend on what happens to the incomes and living costs of households with real expenditures close to the poverty line. The changes in incomes depend on changes in factor returns and the changes in living costs depend on changes in consumer prices. Clearly, a general equilibrium framework is essential for sorting out these complex interactions.

We analyse the general equilibrium effects of the de-urbanisation described above, *ceteris paribus*. De-urbanisation has been one important consequence of the pandemic, but not the only one. Accordingly, we are not attempting to analyse or predict the full social and economic impacts of the pandemic. The latter will depend on many additional factors that remain unknown at the time of writing and are beyond the analytical scope of this analysis, including:

- The continued acceptance by the Indonesian public of restrictions on mobility and social distancing mandated by the government.
- The success of the public health system in treating those infected with the virus.
- The availability, acceptance, effectiveness and timing of vaccines.
- The possible spread of mutant strains of the virus that are more transmissible and possibly even resistant to vaccines.
- The success of the government's social protection program, including its rate of implementation and reach to social groups negatively affected.
- The extent to which a pandemic-induced global economic slowdown affects the rate of recovery of the Indonesian economy.

 The rate at which investor confidence recovers once the pandemic itself is contained.

Section 2 describes the long-term processes of Indonesia's urbanisation and structural change extending over the past five decades. Section 3 briefly summarises previous international attempts to model the general equilibrium impacts of COVID-19. It then summarises what is known about the de-urbanisation and reverse structural change resulting from a year of pandemic, from early 2020 to early 2021. Section 4 describes the general equilibrium approach used in the present paper to analyse the effects of de-urbanisation, including the shocks applied to the model and the closure employed. Section 5 discusses the results, focusing in particular on simulated effects on household welfare, poverty and inequality. In particular, we wish to know how urban and rural households are affected by the general equilibrium consequences of de-urbanisation and whether these findings change the popular view that urban households suffer the largest economic damage. Section 6 shows the results of varying key parametric assumptions and the final section concludes.

2. Structural change, urbanisation and de-urbanisation

Historical trend of rural to urban migration

Urbanisation has been a massive component of Indonesia's economic development. The share of the population living in urban areas rose from 19% in 1976 to 53% in 2017 (Figure 1). According to World Bank projections made in 2016, this share was expected to increase to 71% by 2030 (World Bank 2016). The response to the Covid-19 pandemic has interrupted that process with large scale, but presumably temporary urban to rural migration, which we call de-urbanisation. This is not the first instance of these events. The Asian Financial Crisis of 1997 to 1999 induced a similar response. Agriculture serving as an economic shock

absorber was the way Warr (1999) characterised this phenomenon. In the mid-2000s a similar de-urbanisation occurred, apparently induced by a protection-induced increase in food prices (Warr and Yusuf 2014). But the Covid-19-induced de-urbanisation seems to be larger than either.

Agriculture's declining share of GDP and employment

Figure 2 shows the sectoral composition of Indonesia's sectoral output (value-added) in agriculture, industry and services from 1976 to 2017 using data from the Indonesian government's Central Bureau of Statistics. Over this 41 year interval, agriculture's share of GDP (agricultural value-added / GDP) declined from 23 % to 13 %. At the same time, the share of services rose from 28 to 45 %. That is, all of the decline in agriculture's share of output, and more besides, was taken up by an increase in the share of services.

These calculations are similarly surprising when conducted in terms of employment shares. The data are shown in Figure 3. Over the same period, agriculture's employment share contracted by 29 percentage points, from 61 % in 1976 to 32 % in 2017, while the share of services rose by 19 percentage points and the share of industry rose by 10 percentage points. Abstracting from temporary unemployment, for every 100 workers leaving agriculture, 34 relocated to industry and 66 to services. Structural transformation was a huge economic event, but 'industrialisation' does not describe it accurately. In both output and employment terms, the relative size of agriculture contracted greatly, but the corresponding expansion was primarily in services, not industry.

3. Modelling the pandemic

Previous CGE modelling studies

During 2020, several general equilibrium analyses attempted to project the magnitude of the economic contraction that the pandemic might produce. None of these studies discussed the de-urbanisation that is the focus of the present paper. In an early and preliminary attempt to show the range of possible global outcomes from the pandemic, released in February, McKibbin and Fernando (2020) applied the G-cubed dynamic global economic model. This study applied several alternative but not mutually exclusive characterisations of the economic shock caused by the pandemic: reduced aggregate labour supply due to mortality and morbidity; rising cost of doing business in each sector in each country; reduced consumer spending by commodity due to changing preferences; and increased risk premia by sector and by country. Seven scenarios were constructed, based on different hypothetical assumptions about the quantitative distribution of the above shocks across sectors and across countries.

In a study released in April, Maliszewska *et al.* (2020), used the World Bank's ENVISAGE model, calibrated to GTAP version 10A to make similar global projections, but under very different assumptions. The model, used in comparative static mode, specified a closure with exogenous labour supply and wages adjusting to clear labour markets. The return to capital was fixed and the supply of capital was endogenous. The shocks applied to this model were: an exogenous 3 per cent drop in employment; a 25% increase in all international trade costs, arising whenever goods or services cross borders; a drop in international tourism, captured via a 50% consumption tax on all international tourism-related services; a 15% contraction in demand households away from services requiring close human interaction, including mass transport domestic tourism, restaurants and recreational activities.

In May, the Asian Development Bank (2020) released a study using the GTAP global general equilibrium model. The pandemic shock was represented as: travel bans between 3 and 6 months' duration; cuts in consumption growth by country; cuts in investment growth

by country; increases in trade costs of 1 to 2 per cent; and macroeconomic stimulus applied as subsidies to consumers and producers. The projected GDP impact on Southeast Asia was a 1.5 per cent to 2.5 per cent deviation from the non-COVID-19 baseline, depending on the assumed duration of the containment period. These projected impacts were substantially larger than the GTAP-based projections published a month before, in the ADB's *Asian Development Outlook* 2020.

In each of the above studies, the models were used to project changes in GDP relative to the baseline. Indonesia was one of the countries included in these projections, except for the ADB study, which specified Southeast Asia, including Indonesia. Regrettably, the actual contraction in GDP relative to baseline subsequently reported for Indonesia during 2020 far exceeded the largest of the projections. The pandemic has proven to be even more damaging than expected. All of these modelling studies faced the analytical problem of constructing shocks that might represent the pandemic. Inevitably, because so little was known at the time about the pandemic's economic features, arbitrary and hypothetical guesses had to be made regarding them. The assumed shocks varied widely and although all seemed intuitively plausible, the shocks lacked any empirical basis. In early 2021, a year into the crisis, much more is known about these matters and it should be possible to do better.

Empirically-derived labour market shocks

In this study, we derive the shocks representing Indonesia's de-urbanisation directly from labour market data, rather than arbitrary guesses. As noted above, data from the Indonesian government's *Labour Force Survey* indicate that between August 2019 and August 2020, open unemployment did not change greatly. But over the same period, recorded underemployment increased significantly. Under-employment means those employed but working

less than 35 hours per week. The number under-employed in urban areas increased over this period from 4.4% to 8.4% of the urban workforce. Their hours of work averaged 20.6 per week compared with 50.4 hours for those not under-employed, implying a 2.4 per cent reduction in work time due to under-employment. Rural areas include service activities also affected by the pandemic and under-employment also increased, from 8.9 to 12.4 per cent of the rural workforce. Average hours worked were 21.3 among those under-employed and 48.7 among those not, implying a 2.1 per cent reduction in work time due to under-employment.

The data also indicate a large shift of employment from urban to rural activities between August 2019 and August 2020. We convert the 16 labour force categories identified in the Labour Force Survey into the four labour categories identified in our model: agricultural labour, unskilled formal, unskilled informal and skilled labour. These calculations imply a 7.8% increase in employment of agricultural labour, and reductions in employment of the other three categories of 6.7%, 5.0% and 3.3%, respectively.²

We interpret these data as indicating two labour market shocks that comprise the deurbanisation induced by the pandemic:

Shock 1: A reduction in labour productivity among the urban and rural workforces of 2.4 and 2.1 per cent, respectively.

Shock 2: A shift of labour supply from predominantly, but not exclusively, urban categories (unskilled formal, unskilled informal and skilled) to the rural category (agricultural labour) in the proportions indicated above.

These shocks form the basis for Simulations 1 and 2, described below.

¹ https://sirusa.bps.go.id/sirusa/index.php/indikator/43

² In this classification, 'formal' means paid and 'informal' means unpaid.

4. General equilibrium modelling framework

Model structure

The analysis uses an applied general equilibrium model of the Indonesian economy called INDONESIA-E3F, a 5 sector model aggregated from the 41 sector model INDONESIA-E3 (Yusuf 2006, 2008) for the purpose of this study. Most structural features are standard. Its distinctive characteristic is its disaggregated household structure, designed to facilitate analysis of the way exogenous shocks affect poverty and inequality. The model identifies two categories of households, rural and urban, each of which is divided into 100 subcategories of equal population size, with the sub-categories sorted by expenditures per capita.

The microeconomic behaviour assumed is competitive profit maximization on the part of firms and competitive utility maximization on the part of consumers. Except where otherwise stated, in the simulations reported in this paper the markets for final outputs, intermediate goods and factors of production are all assumed to clear at prices that are determined endogenously within the model. The nominal exchange rate between the Indonesian currency (the rupiah) and the US dollar can be thought of as being fixed exogenously. The role within the model of the exogenous nominal exchange rate is to determine, along with international prices, the nominal domestic price level. Given that prices adjust flexibly to clear markets, a 1 percent increase in the rupiah/dollar exchange rate will result in a 1 percent increase in all nominal domestic prices, leaving all real variables unchanged.

The 5 industries are agriculture, mining, manufacturing, utilities and construction and services. The structure of the model is based on the ORANI-G model (Horridge 2003) with some modifications, of which the most important is the multi-household feature mentioned above. This feature is fully integrated within the general equilibrium structure and enables the model to capture the way that changes in the economy affect households on the expenditure side, through changes in the prices of goods and services that they buy, and also on the income side, through changes in the returns to factors of production that they own.

The theoretical structure of INDONESIA-E3F is conventional for comparative static general equilibrium models. It includes of the following major components:

- The household supplies of 4 categories of labour agricultural labour, unskilled formal labour (paid), unskilled informal labour (unpaid), and skilled labour are each assumed to be exogenous. Their relationship to the Indonesian Social Accounting
 Matrix labour categories is described in Table 1.
- A factor demand system, based on the assumption of CES production technology,
 relating the demand for each primary factor to industry outputs and prices of each of
 the primary factors. The primary factor cost structure of the five industries are
 summarised in Table 2.
- Household consumption demand systems for each of the 200 households, for each of
 the 5 categories of consumer goods corresponding to the 5 industries. These demand
 functions are derived from the linear expenditure system.
- Leontief assumptions for the demand for intermediate goods. Each intermediate good in each industry is assumed to be demanded in fixed proportion to the gross output of the industry.
- Demands for imported and domestically produced versions of each good,

incorporating Armington elasticities of substitution between the two, as summarised in Table 3.

- A set of export demand functions, indicating the elasticities of foreign demand for Indonesia's exports, also summarised in Table 3.
- A set of equations determining the incomes of the 200 households from their (exogenous) ownership of factors of production, reflecting data derived from the 2008 *Social Accounting Matrix*, the (endogenous) rates of return to these factors, and any net transfers from elsewhere in the system. The sources of average household factor incomes are summarised in Table 4.
- Rates of import tariffs and excise taxes across commodities, rates of business taxes,
 value added taxes and corporate income taxes across industries, and rates of personal income taxes across household types which reflect the structure of the Indonesian tax system, using data from the Indonesian Ministry of Finance.
- A set of macroeconomic identities ensuring that standard macroeconomic accounting conventions are observed.

Social accounting matrix

The Indonesian Social Accounting Matrix 2003 serves as the core database for the INDONESIA-E3F model. Analyses of the distributional impact of policies have in the past been constrained by the absence of a Social Accounting Matrix (SAM) with disaggregated households. Since Indonesia's official SAM does not distinguish households by income or expenditure size, this fact has impeded accurate estimation of the distributional impact of exogenous shocks to the economy or policy changes, such as calculation of inequality or poverty incidence. The SAM used in this paper, is aggregated from a larger, specially constructed SAM, representing the Indonesian economy for the year 2008, with 69 industries,

69 commodities, and 200 households (100 urban and 100 rural households sorted by expenditure per capita). Its detailed composition is described in Yusuf (2006).

Factors of production

The simulations assume that the total supplies of each of the four categories of labour are exogenous but that each category is mobile across industries while capital and land are immobile across industries. These features imply an intermediate-run focus for the analysis, of between one and two years duration. The focus is neither very short-run, or else labour would be less than fully mobile, nor long-run, or else capital and land would be more mobile.

Households

The sources of income of the various households are of particular interest for this study because of their central importance for the distribution of income. Urban and rural households differ considerably in the composition of their factor incomes, particularly regarding labour income. This variation, between and within the rural and urban categories is fully captured by the database used for INDONESIA E-3F. The principal sources of the factor ownership matrix are described in Yusuf (2006).

Table 5 summarises the characteristics of urban and rural households as they relate to poverty incidence. Mean consumption expenditures per capita differ widely between urban and rural households. In the simulations conducted below, poverty incidence is calculated for each of these two household categories, using poverty lines for each category calibrated to match the official levels of poverty incidence for 2019, using official poverty

lines. These rates of poverty incidence in 2019 are summarised in the final column of Table 5. Significant numbers of poor people are found in both categories: 6.6 per cent of the urban population and 12.6 per cent of the rural population, implying that 66 per cent of all poor people within Indonesia reside in rural areas.

Poverty incidence and inequality

The approach to analysing income distribution within a CGE model adopted in this paper is the *integrated multi-household method*. It begins by disaggregating households into a discrete number of categories, arranged by expenditure or income per capita.³ These households are then fully integrated into the general equilibrium structure of the model. This approach has the strong methodological advantage of internal model consistency that is the essential feature of true general equilibrium analyses.

Poverty incidence is calculated in this study as follows. The number of household categories is 100 for rural households and 100 for urban households. The calculation of poverty incidence *ex ante* (before the shock) will be described first. For each of the rural and urban categories the raw data on household expenditures per capita are sorted according to expenditures per capita, from the poorest to the richest, creating a smooth cumulative distribution of expenditures per capita. These data are then divided into centile groups, with equal population in each of the 100 categories. Let y_c be expenditure per capita of a

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³ Warr (2008) used this approach in studying the effects on poverty incidence in Thailand of the 2007-08 food price crisis. Warr and Yusuf (2014a and 2014b) applied it to analysing the effect of food prices and fertilizer subsidies, respectively, in Indonesia.

household of the c-th centile where c = 1, 2, ..., 100. That is, y_1 is the poorest centile group and y_{100} is the richest and by construction, $y_{i+1} \ge y_i$. Poverty incidence is now

$$P(y_c, y_p) = \max \{c | y_c < y_p\} + \frac{y_p - \max \{y_c | y_c < y_p\}}{\min \{y_c | y_c > y_p\} - \max \{y_c | y_c < y_p\}}$$
(1)

where y_p is the poverty line. The first term is simply the highest centile for which expenditure per capita is below the poverty line. The second term is the linear approximation to where poverty incidence lies between centiles c and c+1.

The general equilibrium simulation of the impact of a particular shock generates estimated percentage changes in the distribution of real per capita expenditures. Let \hat{y}_c denote the estimated percentage change in the real expenditure per capita of centile group c, The estimated $ex\ post$ (after the shock) level of real expenditure per capita, as estimated by the general equilibrium model is given by y_c^* , where

$$y_c^* = \left(1 + \frac{\hat{y}_c}{100}\right) y_c \,. \tag{2}$$

Different centile categories may be affected very differently by the shock. Therefore, the ordering of centile groups according to their $ex\ post$ real expenditures per capita may have changed from their $ex\ ante$ ordering. The distribution y_c^* is not necessarily smooth in that it may or may not be the case that $y_{i+1}^* \geq y_i^*$. Accordingly, the method of equation (1) above cannot be applied directly to the distribution y_c^* . The 100 household categories in the ex post distribution y_c^* are now re-sorted according to real expenditures per capita in the same way as described above, to obtain a new distribution y_c^{**} such that $y_{i+1}^{***} \geq y_i^{**}$. The distribution y_c^{**} differs from the distribution y_c^* only by this re-sorting. Because of the re-

sorting, the *i*-th centile group in the re-sorted $ex\ post$ distribution y_c^{**} does not necessarily correspond to the *i*-th centile group in the $ex\ ante$ distribution y_c .

The re-sorted *ex-post* distribution y_c^{**} of real expenditures per capita is then used as the basis for recalculating poverty incidence in the same manner as in equation (1), substituting y_c^{**} for y_c to obtain $P(y_c^{**}, y_p)$. The poverty line is held constant in real terms and so the same real poverty line y_p can be used to calculate poverty incidence in the *ex* ante and *ex post* distributions of real expenditures per capita. The estimated change in poverty incidence after a policy shock (as captured by a simulation of the model) is now

$$\Delta P = P(y_c^{**}, y_p) - P(y_c, y_p). \tag{3}$$

That is, the same method is used to calculate the level of poverty incidence in the sorted *ex ante* and the <u>re-sorted</u> *ex post* distributions. The estimated change in poverty incidence is the difference between them.

The calculation of inequality is similarly based on the comparison of the above ex ante and ex post distributions of real expenditures. A Lorenz curve is constructed for each distribution and Gini coefficients of inequality are calculated numerically from them. The above operations are all automated within the model structure.

5. Simulations and results

Model closure

Since the real expenditure of each household is used as the basis for the calculation of poverty incidence and inequality, the macroeconomic closure must be made compatible with both this measure and with the single-period horizon of the model. This is done by ensuring that the full economic effects of the shocks to be introduced are channeled into current-period household incomes and do not 'leak' in other directions, with real-world

inter-temporal welfare implications not captured by the welfare measure. The choice of macroeconomic closure may thus be seen in part as a mechanism for minimising inconsistencies between the use of a single-period model to analyse welfare results and the multi-period reality that the model depicts.

To prevent these kinds of welfare leakages from occurring, the simulations are conducted with balanced trade (exogenous balance on current account). This ensures that the potential effects of the shock being studied do not flow to foreigners, through a current account surplus, or that increases in domestic consumption are not achieved at the expense of borrowing from abroad, in the case of a current account deficit. For the same reason, real government spending and investment demand for each good are fixed exogenously. The government budget deficit is held fixed in nominal terms. This is achieved by endogenous across-the-board adjustments to the *sales tax rate* so as to restore the base level of the budgetary deficit. The combined effect of these features of the closure is that the full impact of an exogenous shock is channeled into household consumption and not into effects that are not captured within the single period focus of the model.

Shocks

Three simulations are conducted. Simulations 1 and 2 apply the shocks described at the end of Section 3 above. In Simulation 1 the productivity of all labour used in non-agricultural industries (mining, manufacturing, utilities and construction, and services) declines by 2.4 per cent and the productivity of all labour used in agriculture declines by 2.1 per cent. Simulation 2 is implemented by increasing each of the 200 households' supply of agricultural labour by 7.8 per cent of its initial quantity and reducing its supply of unskilled formal, unskilled informal and skilled labour by 6.7, 5.0 and 3.3 per cent, respectively. This ensures that total labour supplies change by these proportions. Simulation 3 is both shocks

applied together. Because of the linearity of the model, the results of Simulation 3 are sum of the results of Simulations 1 and 2.

Results

The results are summarised in Tables 6 and 7. It is helpful to interpret Simulations 1 and 2 sequentially. From Table 6, the changes in labour productivity represented in Simulation 1 produce a decline in real GDP, a decline in wages of non-agricultural labour and a rise in agricultural wages. These wage effects then provide a partial incentive for the shift between labour categories that are represented in Simulation 2, but the primary incentive was the absolute contraction in urban sector jobs, together with the virtual impossibility of obtaining alternative urban jobs. The source of these events was the government restrictions imposed (mainly in urban areas) to contain the spread of infection. The shift of labour away from urban employment categories and towards agricultural labour is a household adjustment that occurred in response to these changes. This is de-urbanisation.

The shift in labour supply captured in Simulation 2 causes real GDP to decline again, by a similar amount to Simulation 1. The decline occurs because the shift of labour from higher productivity urban employment to lower productivity agricultural employment is economically inefficient. Nevertheless, the decline in real GDP is not the big story. In Simulation 2 agricultural wages fall by 24 per cent and unskilled formal sector wages rise by 12 per cent. These wage effects shift the burden of adjustment to the pandemic away from urban households and towards rural households. This outcome is summarised in Figure 4.

In Simulation 1 the real expenditures of urban households decline more than those of rural households. Further, among both urban and rural households, the poorest households are affected the least. But in Simulation 2 these effects are reversed. Urban households benefit from the increase in urban wages and rural households lose from the competition-induced

reduction in agricultural wages. The latter effect is largest for the poorest rural households – those most dependent on income from labour. The distinction between the two sets of shocks is mainly analytical. The net outcome is the sum of them both, represented by Simulation 3. Both urban and rural households lose, but rural households lose by far the most, especially the poorest.

The simulated impacts on poverty incidence and inequality shown in Table 7 reflect these results. In Simulation 1 poverty incidence increases marginally among both urban and rural households. In Simulations 2 and 3 the increase in rural poverty incidence dominates the impact on poverty incidence at the national level. The Gini coefficient of inequality declines marginally in Simulation 1 for two reasons. First, urban households are on average better-off that rural households and urban households areas are, on average, negatively affected proportionately the most (see real household consumption in Table 6). Between-region inequality (between rural and urban areas) therefore declines. Second, within both urban and rural regions, poor households are affected proportionately less than the better -off. Within-region inequality therefore declines marginally as well.

Inequality rises in Simulations 2, again for two reasons. First, there is a large reduction in average real expenditures in rural areas and an increase in urban areas. Between-region inequality therefore rises. Second, within-region inequality rises markedly within rural areas because the poorest households – those most dependent in wage income – are affected proportionately more than better-off households. These changes are all much larger in Simulation 2. In Simulation 3, the sum of 1 and 2, the effects of Simulation 2 dominate and inequality rises.

The central economic mechanism driving these distributional results is that when labour supplies shift, as in Simulation 2, large wage effects result, especially in agriculture. This happens because within our model, the demand for agricultural labour is inelastic. A 7.8

per cent exogenous increase in agricultural employment is obtained only with a 24 per cent reduction in real agricultural wages, implying a response elasticity of 0.32. This is not the same as the *ceteris paribus* elasticity of demand because in the simulations, prices other than the wage of agricultural labour are changing at the same time. The general equilibrium response elasticity involves both shifts in the conventional, *ceteris paribus* demand function for labour and movements along it. The Appendix derives the relationship between the *ceteris paribus* elasticity of demand for labour of each category in each sector and the parametric assumptions of the model. The *ceteris paribus* elasticity of demand for labour in agriculture implied by our assumptions is -0.23. The sensitivity analysis conducted below explores these issues further.

6. Varying parametric assumptions

In the Appendix it is shown that the parametric assumptions determining the elasticity of demand for labour are the elasticities of substitution among primary factors (σ_F^k) and among labour categories (σ_L^k) . The role of these elasticities within the model is illustrated in Figure 4. The assumed values of these elasticities are derived from the data bases of the GTAP and MONASH models, respectively, as summarised in the footnote to Table 3, but these values are certainly open to question. Table 8 and Figure 6 show the effect of varying these two parameters across the seemingly feasible range.

The dependent variable in the table and the vertical axis in the figure is the percentage change in average rural consumption minus the percentage change in average urban consumption. A negative number means that, on average, rural households suffer proportionately more than urban households, while a positive number means the opposite.

Negatives occur in all combinations of assumptions but one. Only with seemingly large assumed values for both of these elasticities, implying relatively elastic demand functions for

labour (bottom right hand corner of Table 8) does the opposite occur. At least in the short to medium term, that combination of elasticities, implying an elasticity of demand for labour in agriculture of -0.57, seems improbable. We conclude that the findings are robust with respect to these parametric assumptions.

7. Conclusions

In Indonesia, as with other developing countries, the negative health impact of COVID-19 has been largest in urban, rather than rural areas. This urban concentration was also evident in the loss of employment resulting from the government's program of shutdowns, restrictions on mobility and social distancing. In response, there was a huge migration of low-skilled labour from urban to rural areas. We call this phenomenon de-urbanisation. The implications of this overlooked aspect of the pandemic are explored in this paper.

Over the year ending in August 2020, just over half of Indonesia's non-agricultural workers who lost their jobs plus the new entrants to the national workforce became agricultural workers. The other half became unemployed. The agricultural workforce expanded by 7.8 per cent. This shift in labour supply, combined with inelastic demand for agricultural labour, depressed agricultural wages, a major income source for rural households, especially the poorest. We argue that the economic effects of this phenomenon were so large that they reversed the apparent distributional impact of the pandemic. Rural, not urban households became the largest economic losers and within Indonesia as a whole, the poorest households – the rural poor – were the most affected.

These findings have important implications for social protection in Indonesia, a major policy issue in that country. Our results imply that if social protection measures concentrate primarily on the apparent losers from the pandemic – those in urban areas – they will miss the areas of greatest economic hardship.

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Appendix: Elasticity of demand for labour by category and sector

We will derive the *ceteris paribus* elasticity of demand for each category of labour in each sector within this model. As summarised in Figure 4, within each sector there are two levels of constant elasticity of substitution (CES) nesting to be considered: (i) substitution among the three primary factors, composite labour (an aggregate of the four distinct categories of labour defined in Table Z), capital and land; and (ii) substitution among the four categories of labour within the labour composite. We will denote the elasticities of substitution at these two levels within sector k as σ_F^k and σ_L^k , respectively. Let X_i^k be the quantity of labour of category i (i=1,...,4) demanded in sector k (k=1,...,5). Let W_i^k be the wage of labour of of category i in sector i. Since we are not assuming complete mobility of labour, the wage of labour in each category is not necessarily equated across sectors. Let \overline{X}^k be the quantity of composite labour (a CES composite of the four types of labour) and its notional wage be \overline{W}^k . We use lower case Roman letters to denote the proportional changes of variables defined in levels in upper case, so $x_i^k = dX_i^k/X_i^k$ will denote the proportional change of X_i^k , \overline{W}^k will denote the proportional change of \overline{W}^k , and so forth.

Dixon *et al.* (1992, p. 125) show that with a CES production function, the proportional change in the demand for composite labour in sector k is given by

$$\overline{x^k} = y^k - \sigma_F^k (\overline{w^k} - \sum_{i=1}^3 S_{Fi}^k p_i^k), \tag{A.1}$$

Where y^k denotes the proportional change in the output of sector k, S_{Fj}^k denotes the share of primary factor j (one of which is composite labour) in sector k, and $\sum_{j=1}^3 S_{Fj}^k = 1$, and p_j^k denotes the proportional change in the price of primary factor j in sector k. Noting that one of the three primary factors is composite labour, the proportional change in its price is identical to $\overline{w^k}$. Constant returns to scale implies that

$$y^k = \sum_{i=1}^3 S_{Fi}^k x_i^k. \tag{A.2}$$

Recalling that one of the primary factors is composite labour and that the quantities of capital and land are held fixed in each sector, substituting (A.2) into (A.1) and rearranging gives the *ceteris paribus* demand for composite labour

$$\overline{x^k} = -\sigma_F^k \overline{w^k}. (A.3)$$

Thus $\overline{x^k}/\overline{w^k} = -\sigma_F^k$. The *ceteris paribus* elasticity of demand for composite labour is simply the negative of the elasticity of substitution among primary factors.

The proportional change in demand for category i labour (i = 1,...,4) is

$$\chi_i^k = \overline{\chi^k} - \sigma_L^k (w_i^k - \sum_{r=1}^4 S_{Lr}^k w_r^k), \tag{4}$$

where w_r^k denotes the proportional change in the wage of labour of category r in sector k, (r = 1, ... 4) and S_{Lr}^k is the share of labour of category r in total labour cost with sector k. Substituting (A.3) into (A.4) and rearranging gives

$$\chi_i^k = -[\sigma_F^k S_{Ii}^k + \sigma_I^k (1 - S_{Ii}^k)] w_i^k, \tag{5}$$

and the *ceteris paribus* elasticity of demand is $-[\sigma_F^k S_{Li}^k + \sigma_L^k (1 - S_{Li}^k)]$. For each category of labour, this elasticity is a weighted average of $-\sigma_F^k$ and $-\sigma_L^k$. It must lie between these two numbers. As the labour cost share approaches 1, the elasticity of demand approaches $-\sigma_F^k$, as in (A.3). That is, if one category of labour dominates in a sector, the nesting of labour categories becomes less relevant. The ceteris paribus elasticities of substitution implied by the parameters of our model are summarised in Table A.1.

Table A1. Implied elasticities of demand for labour

Sector	Agriculture labour	Unskilled formal labor	Unskilled informal labor	Skilled labor
Agriculture	-0.227	-0.348	-0.349	-0.347
Mining	n.a.	-0.275	-0.329	-0.297
Manufacturing	n.a.	-0.851	-0.478	-0.581
Utilities and construction	n.a.	-1.061	-0.420	-0.589
Services	n.a.	-0.474	-0.426	-1.249

Note: n.a. means not applicable, because agricultural labour is not employed in this sector.

Table 1. Labour categories used, based on Social Accounting Matrix classification

	Labour categories (16) used in Indonesia's SAM	Labour categories (4) used in this model
1	Urban, formal, agriculture	Agricultural
2	Rural, formal, agriculture	Agricultural
3	Urban, informal, agriculture	Agricultural
4	Rural, informal, agriculture	Agricultural
5	Urban, formal, production	Unskilled, formal
6	Rural, formal, production	Unskilled, formal
7	Urban, informal, production	Unskilled, informal
8	Rural, informal, production	Unskilled, informal
9	Rural, formal, clerical	Skilled
10	Rural, formal, clerical	Skilled
11	Urban, informal, clerical	Skilled
12	Rural, informal, clerical	Skilled
13	Urban, formal, professional	Skilled
14	Rural, formal, professional	Skilled
15	Urban, informal, professional	Skilled
16	Rural, informal, professional	Skilled

Note: In the SAM classification, 'formal' means paid and 'informal' means unpaid.

Source: 16 SAM categories from Central Bureau of Statistics, Social Accounting Matrix, Indonesia, 2003, Central Bureau of Statistics, Jakarta, 2003.

Table 2. Primary factor cost shares (Units: per cent total primary factor cost)

Sector	Agricultural labour	Unskilled formal labour	Unskilled informal labour	Skilled labour	Capital	Land	Total
Agriculture	55.0	1.0	0.3	1.6	12.3	29.8	100
Mining	0	9.1	2.6	6.4	59.3	22.7	100
Manufacturing	0	20.6	5.3	9.5	63.4	1.2	100
Utilities & construction	0	27.7	2.8	9.3	60.3	0	100
Services	0	6.4	3.9	46.1	43.7	0	100

Source: Authors' calculations from Indonesia's official SAM and related data sources.

Table 3. Trade shares and principal elasticity assumptions

	Trade sha	ares		Elasticity p	arameters	
Sector	Import (%)	Export (%)	Armington elasticity of demand	Export demand elasticity	Elasticity of substitution among primary factors	Elasticity of substitution among labour categories
Agriculture	4.80	2.00	2.4	5.4	0.22	0.35
Mining	23.50	34.20	5.65	8.4	0.20	0.35
Manufacturing	23.10	22.10	3.09	6.4	1.21	0.35
Utilities and construction	0.00	0.00	2.11	5.8	1.37	0.35
Services	6.00	9.80	1.97	3.8	1.45	0.35

Note: Import share means imports/domestic demand. Export share means exports/domestic production.

Source: Authors' calculations. Armington elasticities, export demand elasticities and elasticities of substitution among primary factors are aggregated from the GTAP database version 8, as described in GTAP database, as described in Hertel (1999). Elasticities of substitution among labour types are aggregated from the MONASH model, as described in Dixon and Rimmer (2002).

Table 4. Average household factor income shares, urban and rural (Units: per cent of mean total household factor incomes)

Sector	Agricultural labour	Unskilled formal labour	Unskilled informal labour	Skilled labour	Capital	Land	Total
Urban	2.9	17.4	4.4	35.8	28.7	10.8	100
Rural	26.2	16.7	5.7	18.6	23.7	9.0	100
Total	11.6	17.1	4.9	29.4	26.9	10.1	100

Source: Authors' calculations from Indonesia's official SAM and related data sources.

Table 5. Expenditure and poverty incidence by household group, 2019

	% of total population in this group	% of total households in this group	Mean per capita expenditure (Rp. /mo.)	% of population in this group in poverty
Urban	49.1	48.6	1,488,442	6.6
Rural	50.9	51.4	884,902	12.6
Total	100	100	1,181,315	9.6

Source: Authors' calculations from Indonesia's Susenas survey and related data sources.

Table 6. Simulation results I: Economic summary

(Units: Percent change)

	Simulation 1	Simulation 2	Simulation
Macroeconomic effects			
Real GDP	-1.020	-1.180	-2.180
Real household consumption	-1.400	-0.835	-2.190
Real household consumption (urban)	-1.680	0.451	-1.190
Real household consumption (rural)	-0.587	-1.780	-2.330
Consumer price index	0.288	-0.785	-0.522
Employment	0.000	-2.630	-2.610
Real factor return effects			
Agricultural labour	1.692	-24.415	-22.978
Unskilled labour formal	-1.011	11.885	10.922
Unskilled labour informal	-1.274	6.685	5.442
Skilled labour	-0.946	2.625	1.732
Capital	-1.148	2.805	1.722
Land	-4.058	3.235	-0.738
Sectoral output effects			
Agriculture	-1.190	3.840	3.840
Mining	-0.089	-0.351	-0.351
Manufacturing	-1.100	-2.470	-2.470
Utilities and construction	-0.614	-2.150	-2.150
Services	-1.330	-2.030	-2.030
Consumer price effects			
Agriculture	0.161	-9.040	-9.060
Mining	-0.429	-0.987	-1.410
Manufacturing	0.069	0.505	0.573
Utilities and construction	0.493	2.550	3.070
Services	0.743	1.530	2.310

Note: Simulation 3 is Simulations 1 and 2 together. Because of model linearity, the results of Simulation 3 are the sum of those of Simulations 1 and 2.

Source: Authors' calculations.

Table 7. Simulation results II: Poverty and Inequality

	Simulation 1	Simulation 2	Simulation 3
Poverty incidence (Units: Pe	ercent of relevant population	on)	
Urban poverty incidence			
Ex-ante level	6.560	6.560	6.560
Ex-post level	6.764	6.726	6.950
Change	0.204	0.166	0.390
Rural poverty incidence			
Ex-ante level	12.600	12.600	12.600
Ex-post level	12.734	14.015	14.129
Change	0.134	1.415	1.529
Total poverty incidence			
Ex-ante level	9.593	9.593	9.593
Ex-post level	9.762	10.386	10.555
Change	0.169	0.793	0.962
Gini coefficient of inequality	(Units: Gini index)		
Urban Gini index			
Ex-ante	0.369	0.369	0.369
Ex-post	0.367	0.369	0.368
Change	-0.001	0.000	-0.001
Rural Gini index			
Ex-ante	0.277	0.277	0.277
Ex-post	0.275	0.286	0.284
Change	-0.002	0.008	0.006
Total Gini index			
Ex-ante	0.371	0.371	0.371
	0.369	0.377	0.375
Ex-post	0.507		

Note: See note to Table 6.

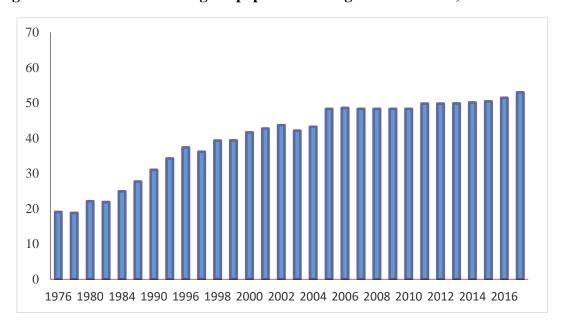
Source: Authors' calculations.

Table~8.~Simulated~percentage~change~in~average~rural~consumption~minus~average~urban~consumption~when~elasticity~of~substitution~assumptions~vary

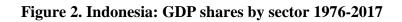
Among primary		Amon	g labour categories	$\sigma(\sigma_L^k)$	
factors (σ_F^k)	0.2	0.375	0.55	0.725	0.9
0.12	-2.65	-2.38	-2.16	-1.96	-1.8
0.24	-1.15	-1.02	-0.912	-0.807	-0.716
0.36	-0.627	-0.535	-0.458	-0.381	-0.312
0.48	-0.362	-0.287	-0.223	-0.159	-0.102
0.60	-0.202	-0.136	-0.081	-0.024	0.027

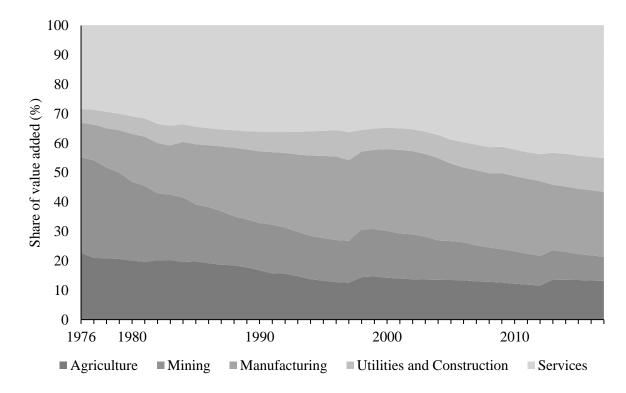
Source: Authors' calculations.

Figure 1. Indonesia: Percentage of population living in urban areas, 1976 to 2017

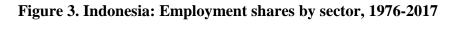


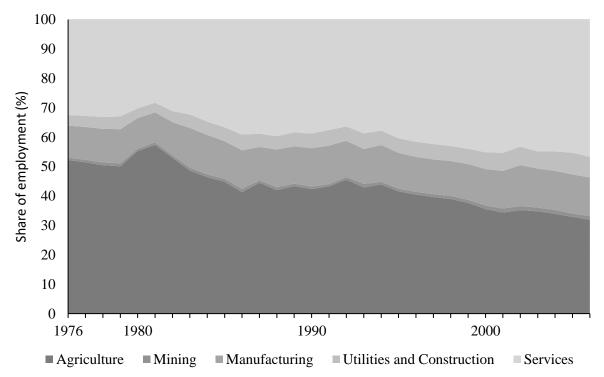
Source: Authors' calculations, using data from Central Bureau of Statistics, Jakarta.





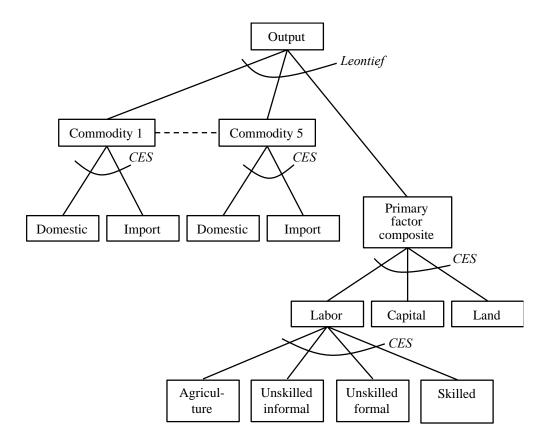
Source: Authors' calculations, using data from Central Bureau of Statistics, Jakarta.





Source: Authors' calculations, using data from Central Bureau of Statistics, Jakarta.

Figure 4. Production structure



Source: Authors' construction.

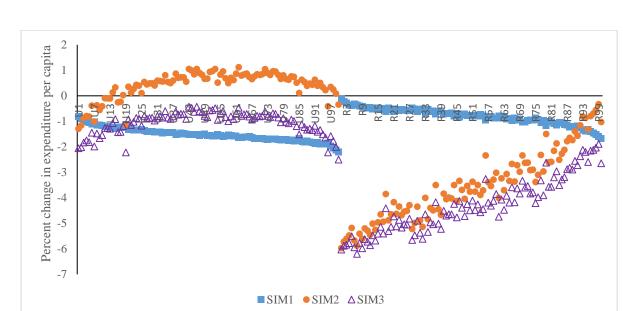
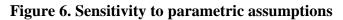
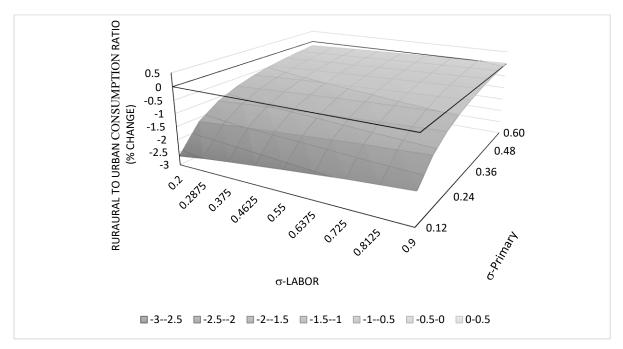


Figure 5. Change in real household expenditures per person: Simulations 1, 2 and 3

Note: The horizontal axis shows, from the left, the 100 urban households, arranged from the centile with lowest initial level of expenditure per person (U1) to the highest (U100), and then the 100 rural households, (R1 to R100), arranged in the same way. The vertical axis shows the simulated percentage change in each household's real expenditure per person.

Source: Authors' calculations from simulation results.





Source: Authors' calculations from simulation results.