Who Suffers from the COVID-19 Shocks?
Labor Market Heterogeneity and Welfare Consequences in Japan *

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November 19, 2020

Abstract

Effects of the COVID-19 shocks in the Japanese labor market vary across workers of different age groups, genders, employment types, education levels, occupations, and industries. We document heterogeneous changes in employment and earnings in response to the COVID-19 shocks, observed in various data sources during the initial months after the onset of the pandemic in Japan. We then feed these shocks into a life-cycle model of heterogeneous agents to quantify welfare consequences of the COVID-19 shocks. In each dimension of the heterogeneity, the shocks are amplified for those who earned less prior to the crisis. Contingent workers are hit harder than regular workers, younger workers than older workers, females than males, and workers engaged in social and non-flexible jobs than those in ordinary and flexible jobs. The most severely hurt by the COVID-19 shocks has been a group of female, contingent, low-skilled workers, engaged in social and non-flexible jobs and without a spouse of a different group.

Keywords: COVID-19, Japan, labor market, welfare effect, life-cycle model, inequality
JEL Classification: E21, E24, J31

*We thank Anton Braun, Daiji Kawaguchi, Masayuki Morikawa, Makoto Nirei, Koki Okumura, Etsuro Shioji, Kazunari Tanabe, Satoshi Tanaka, Hajime Tomura, Yuichiro Waki, and participants of the seminar at Waseda University for helpful comments. We are also grateful to the anonymous referee for many valuable suggestions. We acknowledge financial support from the Center for Advanced Research in Finance (CARF) at the University of Tokyo. This study is conducted as a part of the research at the Research Institute of Economy, Trade and Industry (RIETI).

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1 Introduction

The COVID-19 pandemic has brought significant shocks to the labor markets all over the world, and Japan is no exception. While Japan did not see a sharp increase in unemployment rate immediately after the onset of crisis, which stood at 2.6% in April 2020, compared to other countries such as 14.9% in the United States in April 2020, shocks in the labor market are spread highly unequally across workers.[1,2] In this paper, we first document heterogeneous responses in employment and earnings to the COVID-19 shocks observed during the initial months after the onset of the crisis in Japan. We then feed these shocks in the labor market into a life-cycle model of heterogeneous agents to quantify welfare consequences of the COVID-19 shocks.

Despite the relatively small change in the overall unemployment rate, we find that negative effects of the COVID-19 shocks significantly differ across individual workers, in various dimensions including age group, gender, employment type, education level, occupation, and industry. Moreover, in each dimension, the shock is larger for those who earned less prior to outbreak of the pandemic, amplifying inequality in the labor market across multiple dimensions.

To quantify welfare effects from the COVID-19 shocks, we build a life-cycle model and let heterogeneous individuals face unexpected changes to their earnings and employment, as observed in the data, and have them re-optimize in response to the shocks. We evaluate welfare effects on different types of individuals in terms of consumption equivalent variation that would make them as better off as before in the economy without the COVID-19 shocks.

Our findings can be summarized as follows. First, contingent workers suffer significantly, up to more than three times as much as regular workers in terms of our welfare measure. They are more severely hurt in both employment and wages than regular workers, and we find that employment type is one of the most critical dimensions that divides the fate of individuals in the labor market after the crisis. Second, we also find that younger generations suffer more than older generations. Third, female workers fare worse than males. The difference is mainly due to the fact that the share of contingent workers is larger for females, but also because females are more concentrated in jobs that are more severely affected by the COVID-19 shocks. Forth, workers in social sectors and/or non-flexible occupations suffer more. The COVID-19 crisis differs from past recessions such as

[1] The Japanese unemployment rate is from the Labor Force Survey (LFS) of the Ministry of Internal Affairs and Communications (MIC). The U.S. unemployment rate is from the Labor Force Statistics of the Current Population Survey (CPS). The U.S. unemployment rate peaked in April and declined to 13.3% and 11.1% in May and June, respectively. The Japanese unemployment rate has been relatively stable during the period with 2.9% in May and 2.8% in June, respectively.

[2] Kikuchi et al. (2020) discuss heterogeneity of potential vulnerability of workers to the COVID-19 shocks using data prior to the crisis.

the financial crisis of 2008 in that it contracts economic activities in sectors that involve more face-to-face transactions and occupations involving tasks difficult to be completed remotely from homes or in physical isolation from other people. Kikuchi et al. (2020) discussed heterogeneous vulnerability across occupations and industries and pointed to risks of rising inequality, which we confirm has manifested in wage and employment changes across workers in the data during the first months after the crisis.

We also stress a caution in the interpretation of our quantitative results. As discussed above, the main focus of our paper is to assess changes in the labor market during the initial months after the onset of the COVID-19 crisis, which we observed in various official data, and to quantify welfare implications from these observations. For this purpose, we build a simple life-cycle model of heterogeneous agents that enables us to focus on the analysis of these effects in the short-run. There is, however, significant uncertainty about whether various shocks we currently observe will be short-lived or long-lived and whether they will be repeated multiple times over years to come. We evaluate welfare effects under some scenarios about the duration of shocks and our results may need to be re-examined when more data is available and there is less uncertainty as to the magnitude and the duration of the pandemic.[3]

Moreover, there may well be other structural changes in the economy that the COVID-19 crisis may induce over the medium and long-run. There are also many changes that the Japanese economy had been going through, including changes in the composition of employment type and gender-specific involvement in the labor market, aging demographics, fiscal challenges associated with rising expenditures on the social insurance system. The COVID-19 crisis may interact with these changes and possibly amplify challenges that Japan is faced with in some dimensions, or hopefully mitigate them in other dimensions. Although we acknowledge these topics and potential consequences of the COVID-19 crises in the medium and long-term as very important and worth exploring, they are not in the scope of the current analysis, and our model intentionally abstracts from them. Our focus is on a quantitative evaluation of shocks in the labor market immediately after the crisis hit the economy, and we do not explicitly discuss or evaluate specific policies.[4]

Numerous studies have emerged that investigate heterogeneous consequences of the COVID-19 shocks on individuals and implications for welfare and policies, which include but are not limited to Acemoglu et al. (2020), Alon et al. (2020a), Glover et al. (2020), Kaplan et al. (2020b), and Albanesi et al. (2020), just to name a few.[5] Our study

[3]Some papers including Kawaguchi and Murao (2014), Guvenen et al. (2017) and Huckfeldt (2016) argue that recessions could have lasting scarring effects on a vulnerable group of workers, especially on the young.

[4]See Ando et al. (2020) for a comprehensive overview of various policies implemented by the Japanese government in response to the COVID-19 shocks.

[5]Other papers that document and study early responses to the COVID-19 shocks in the U.S. labor market include Coibion et al. (2020), Gregory et al. (2020) and Kahn et al. (2020).

complements the literature by documenting facts and analyzing welfare consequences in Japan.

This paper is also complementary to studies of various economic aspects of the COVID-19 shocks in Japan. They include Fukui et al. (2020) on the impact of pandemic on job vacancy postings, Watanabe and Omori (2020) on consumption responses across sectors, Miyakawa et al. (2020) on firm default, Kawata (2020) on occupational and spatial mismatch, Kawaguchi et al. (2020) on uncertainty faced by small and medium-sized firms, and Okubo (2020) on implementation of telework across occupations.

The rest of the paper is organized as follows. Section 2 provides an overview of economic shocks triggered by the COVID-19 shocks observed in the early data and lays out facts that our model analysis in the following sections is focused on. Section 3 presents our dynamic life-cycle model and section 4 discusses parametrization of the model. Numerical results are discussed in section 5 and section 6 concludes. The appendices provide more details about the data sources and discusses our computation methods.

2 Impact of the COVID-19 Shocks on the Labor Market in Japan

This section documents changes in employment and earnings during the COVID-19 crisis. The data source of our analysis is mainly Labor Force Survey (LFS) data for monthly employment, and is supplemented by Monthly Labor Survey (MLS) data for monthly earnings and Employment Status Survey (ESS) data in 2017 for composition of workers across different categories.

2.1 Data Sources

We provide a brief explanation of the three labor market data sources: LFS, MLS, and ESS below. Detailed description of these data sets is provided in appendix A.

Labor Force Survey (LFS): The LFS is a monthly cross-sectional household survey conducted by the Ministry of Internal Affairs and Communications (MIC). It covers approximately 40 thousand households across the nation and collects detailed information about the employment status of household members. We use publicly available tabulated data to compute employment by age, gender, employment type, industry, and occupation.

Monthly Labor Survey (MLS): The MLS is a monthly cross-sectional monthly survey conducted by the Ministry of Health, Labour and Welfare (MHLW), which covers approximately 33 thousand establishments and their employees from the private and public sectors. We use publicly available tabulated data to compute earnings by employment type and industry.

Employment Status Survey (ESS): The ESS is a cross-sectional household survey conducted every five years by the MIC. For our research purpose, we use the latest data collected in October 2017. It is one of the most comprehensive surveys on employment circumstances in the nation. It covers approximately 490 thousand households and provides detailed information about the demographic characteristics of households, employment and unemployment situations, and descriptions of current jobs held by household members. We use the "order-made" summarization system to compute joint distribution of workers and earnings prior to the crisis, across age groups, genders, education levels, employment types, occupations, and industries.[6]

Besides the three data sources for labor market statistics, we also use the Family Income and Expenditure Survey (FIES) data for changes in consumption level and allocations. More details about the data sources are provided in appendix A.

2.2 Classification of Workers

We briefly explain below how we classify workers according to three different dimensions: employment type, industry and occupation. More details about the classifications in each of the data sources are given in appendix A.

Employment-Type Categories: Employment in the Japanese labor market is characterized by a distinction in employment type: regular or contingent employment. How they are termed in the Japanese language differs depending on situations and data source. In the ESS, for example, regular employment includes executives of companies and staff members who are termed regular (*seiki*) employees. Contingent (*hiseiki*) employment includes part-time workers, albeit (temporary workers), dispatched workers, contract employees and others. Contingent workers are sometimes termed irregular or non-regular workers as well.[7]

The distinction is different from that between full-time and part-time workers in other countries. Contingent workers may well work for the same number of hours as regular workers but they tend to receive lower wages, fewer fringe benefits, and much less job security than regular workers. As documented in papers such as İmrohoroğlu et al. (2016) and Kitao and Mikoshiba (2020), earnings of contingent workers are much lower among

[6]The ESS data is based on statistical products provided by the Statistics Center, an independent administrative agency based on the Statistics Act, as a tailor-made tabulation of the 2017 ESS compiled by the MIC.

[7]How workers are divided into the two employment types in each database we used is explained in appendix A.

both males and females. Females have a higher fraction of contingent workers than males and so do less educated workers than those with higher education. Moreover and most importantly, contingent workers are subject to more frequent employment adjustment and job instability, as shown in empirical studies including Esteban-Pretel et al. (2011) and Yokoyama et al. (2019). In the analysis below, we include employment status as one of the key dimensions of heterogeneity across workers in evaluating effects of the COVID-19 crisis.

Sectoral Categories: The second dimension along which we classify workers is industry. The COVID-19 crisis invokes urgent need to suppress economic activities that require personal interactions, in order to control the infections. Workers in industries that produce goods and services that involve a large amount of personal and face-to-face interactions are affected more severely by the COVID-19 shocks. This is in a unique feature of the COVID-19 crisis, leading to a group of damaged industries that differ from a typical set of industries that are more likely to be hit by regular recessions.

Following Kaplan et al. (2020b), we group industries into two sectoral categories: ordinary and social.[8] Based on the distribution of workers across sectors in the ESS, 48% of total employment is classified into the ordinary sector, and the remaining 52% is classified into the social sector, prior to the COVID-19 shocks.

- Ordinary Sector: agriculture, forestry and fisheries; mining, quarrying of stone and gravel; electricity, gas, heat supply and water; construction; manufacturing; wholesale; transport and postal activities except for railway, road passenger and air transport; postal service; information and communications; finance and insurance; real estate, goods rental and leasing.

- Social Sector: retail trade; railway, road passenger and air transport; education and learning support; medical, health care and welfare; living-related, personal and amusement services; accommodations, eating and drinking services; scientific research, professional and technical services; cooperate associations, n.e.c.; services, n.e.c.; government.

Note that not all data sources provide sector information of the same accuracy, and we use a broader classification for the MLS. Also, we use a slightly different categorization for the expenditure data from the FIES. For more details, see sections A.2 and A.4, respectively.

[8] We use industrial categories defined in the Japan Standard Industrial Classification (JSIC), as revised in 2013. Although we follow the classification of Kaplan et al. (2020b), their classification according to the NAICS does not match exactly our classification in the ESS based on the JSIC. See appendix A for more details of our industry classification. Please note that Kaplan et al. (2020b, 2020a) use the term "regular" industries to denote what we call "ordinary" industries here. "Regular" is used to represent one of two employment types in this paper.

Occupational Categories: Finally, we classify workers by occupations and group them into two occupational categories, flexible and non-flexible occupations, based on the fraction of workers in each occupation who are likely to work remotely and less affected by difficulty in commuting to and working in their regular workplace.[9] Following Mongey et al. (2020), we construct measures of the fraction of flexible-type workers in each occupation. Figure 1 shows the result. We then classify occupations as flexible if the measure is larger than 0.75. As a result, 60% of total employment is classified into flexible occupation, and the remaining 40% is classified into non-flexible occupation.

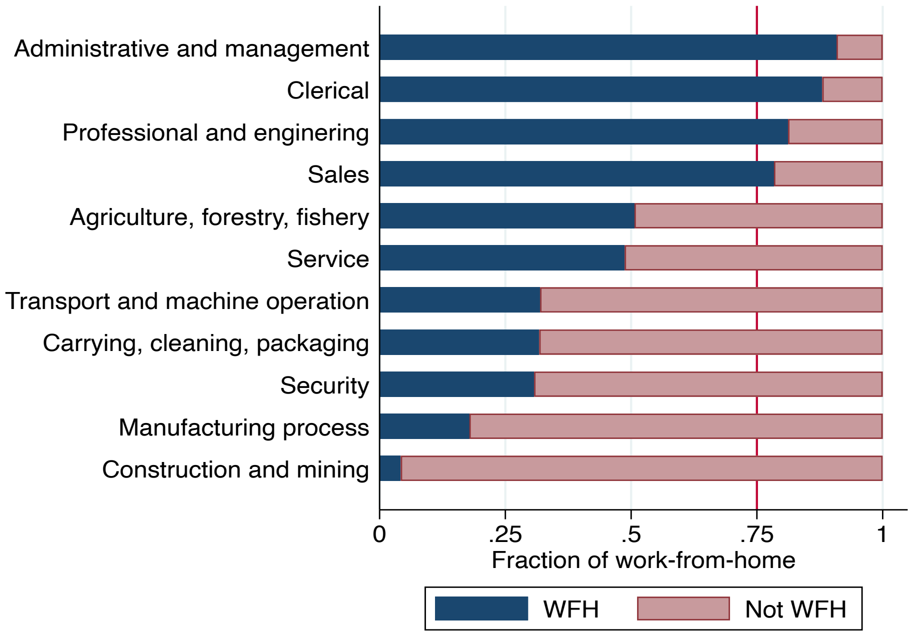


Figure 1: Work-from-home Measures: JSOC

Note: This figure shows the fraction of workers who are able to work from home in each occupation. To compute the measure, we follow Mongey et al. (2020) and convert the Standard Occupational Classification (SOC) to the Japan Standard Occupational Classification (JSOC).

- Flexible Occupation: administrative and management; clerical workers; professional and engineering workers; sales workers.
- Non-flexible Occupation: agriculture, forestry and fishery workers; service workers; transport and machine operation workers; carrying, clearing, packaging and related workers; security workers; manufacturing process workers; construction and mining workers.

[9]We use occupational categories defined in the Japan Standard Occupational Classification (JSOC), as revised in December 2009.

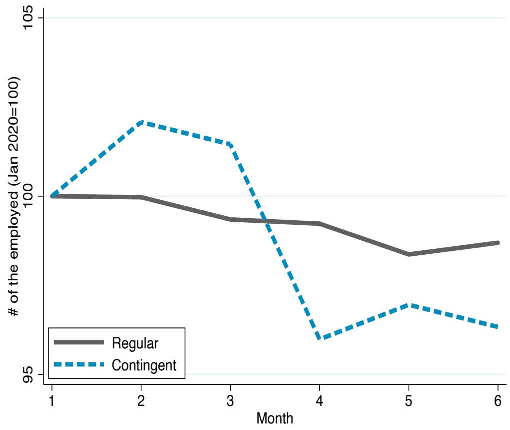
2.3 Changes in Employment

This section documents changes in employment in Japan during the COVID-19 crisis. The data source is LFS data for most of the analysis, and ESS data for compositional analysis.[10]

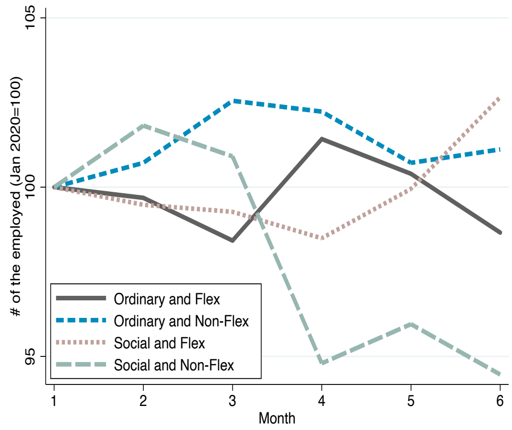
By Employment Type, Sector and Occupation: Figure 2a shows the number of employed by employment type (regular and contingent). We normalize to 100 the level of employment for each type in January 2020. While regular workers' employment declined by around 1% in April, May, and June compared to January, contingent workers' employment declined more sharply by around 4%. An observation that employment of contingent workers responds more to shocks is consistent with previous crisis episodes in Japan where contingent workers have been more vulnerable to business cycle shocks, as documented by Yokoyama et al. (2019).

Figure 2b shows the number of employed according to the sectoral and occupational categories defined above. The number of workers in the social sector and non-flexible occupations declined the most, by more than 5% from January to April 2020, and it remains low until June. The difference across sectors and occupations highlights the importance of the feasibility of completing work from home, as emphasized by Dingel and Neiman (2020) in the case of the US labor market and Fukui et al. (2020) based on changes in the pattern of job vacancy postings in Japan after the COVID-19 shocks.

[10] Note that the monthly data series presented in sections 2.3 are raw data and not seasonally adjusted and changes include potentially seasonally factors. See appendix D for seasonally adjusted versions of the same figures.



(a) By Employment Type



(b) By Sector and Occupation

Figure 2: Changes in Employment (Jan. 2020 = 100)

Note: Figure 2a shows the number of employed by employment type in each month between January and June 2020, based on samples of workers aged 25 to 64. Figure 2b shows the number of employed by sector and occupation categories. The samples include workers aged 15 to 64, differently from Figure 2a, since data by more granular categories is not available from the publicly available aggregate data. For the same reason, samples in Figure 2b include not only regular and contingent workers but also other types of workers such as the self-employed. In both figures, the values in January 2020 are normalized to 100, and series are not seasonally adjusted. The data is from Labor Force Survey (LFS) by the Ministry of Internal Affairs and Communications (MIC).

By gender: Figure 3 shows changes in the number of employed by gender, where the level in January 2020 is normalized to 100. While both males' and females' employment declined since February 2020, the decline is larger for females. This is similar to what occurred in the U.S. where female workers were hit harder by the COVID-19 shocks than male workers, as emphasized by Alon et al. (2020a).

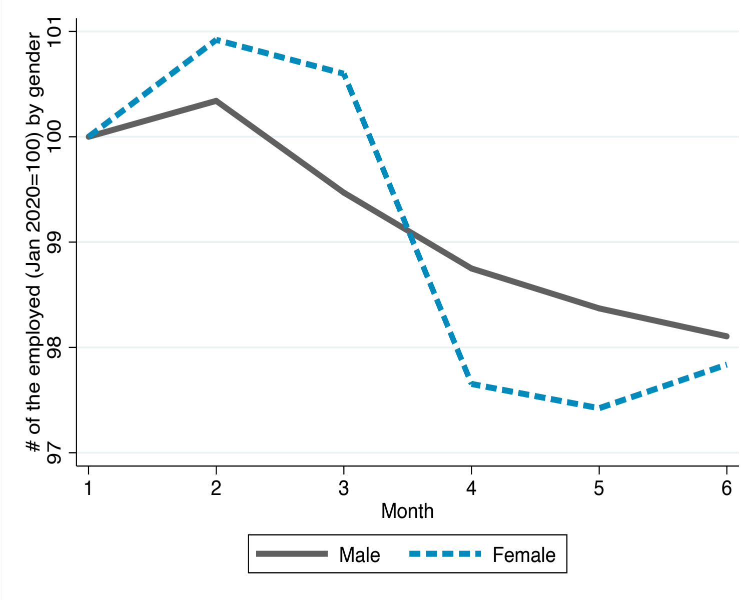


Figure 3: Changes in Employment by Gender (Jan. 2020 = 100)

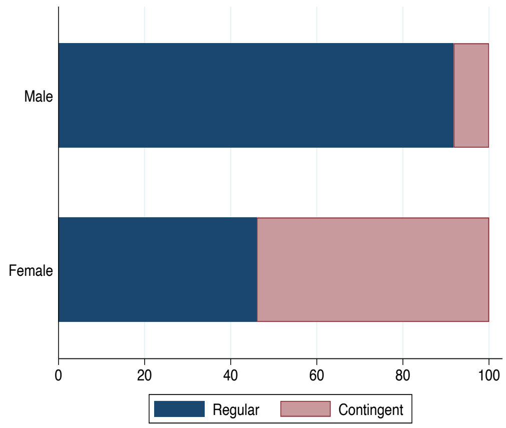
Note: Figure 3 shows the number of employed by gender in each month between January and June 2020. We restrict samples to workers aged 25 to 64. The values in January 2020 are normalized to 100, and series are not seasonally adjusted. The data is from Labor Force Survey (LFS) by the Ministry of Internal Affairs and Communications (MIC).

Why have female workers suffered more from the COVID-19 shocks? Figure 4 shows the characterization of workers by gender based on the ESS data prior to the COVID-19 crisis. Figure 4a displays the share of contingent workers out of total employment by gender. While the share of contingent workers is less than 10% for males, more than 50% of female workers work a contingent job. This difference partially contributes to larger decline for female employment, since contingent workers are subject to more employment adjustment during economic downturns as discussed above, and in fact, there was a larger decline in employment among contingent workers as we show below.

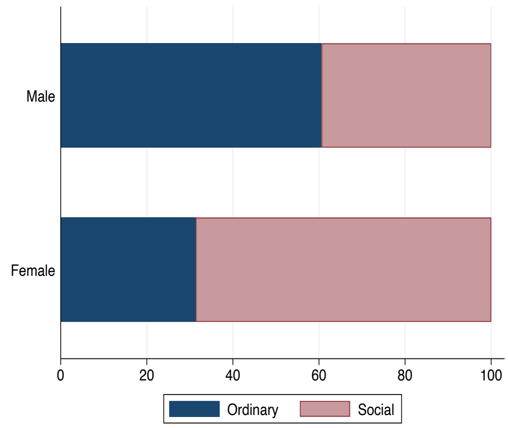
Figure 4b shows the share of workers in the social sector out of total employment by gender. Again, female workers are more concentrated in the social sector (69%) than male workers (39%). Figure 4c shows the share of workers in non-flexible occupations out of total employment by gender. In contrast to employment type and sector, male workers appear to be more vulnerable in terms of the non-flexibility of the work arrangement, though the difference is relatively small.[11] Figure 4d, however, which shows the joint distribution of employment across sectors and occupations, reveals that the share of the most vulnerable workers engaged in social *and* non-flexible jobs is higher for females than males. The share of the least vulnerable workers in ordinary and flexible jobs is larger for

[11]The share of non-flexible occupations is 46% for males and 34% for females.

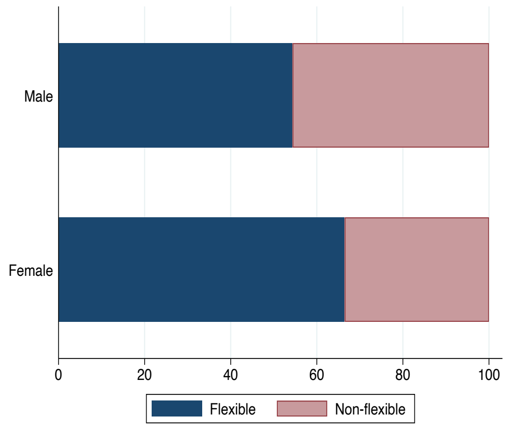
males than females as well.



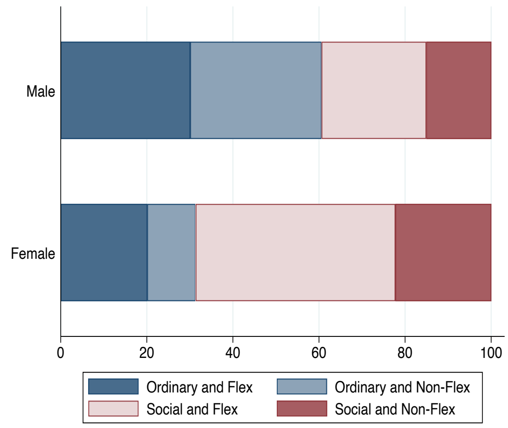
(a) By Employment Type



(b) By Sector



(c) By Occupation

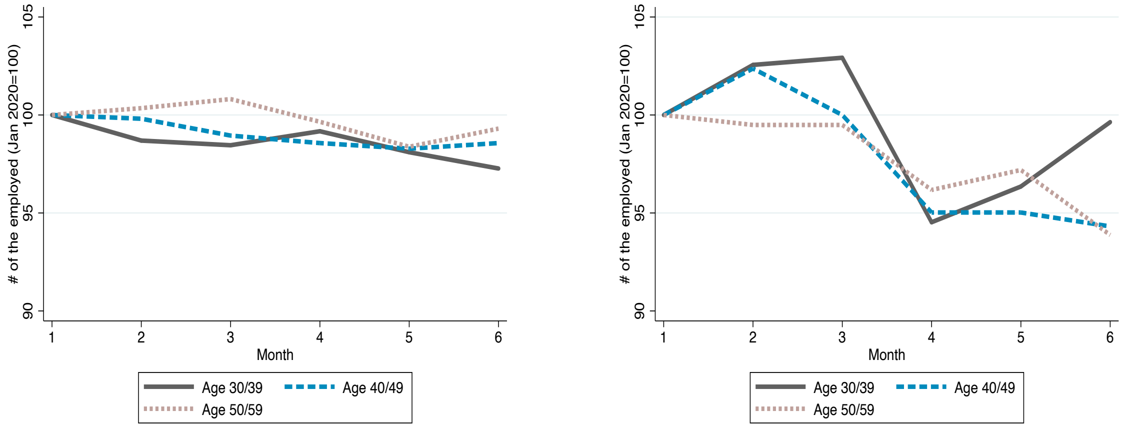


(d) By Sector-Occupation

Figure 4: Share of Each Characteristics by Gender

Note: Figure 4 shows the employment share for each characteristic by gender. We restrict samples to workers aged between 30 and 59 because the data is available only for 10-age bin. The data is from Employment Status Survey (ESS) conducted in 2017 by the Ministry of Internal Affairs and Communications (MIC).

By Age Group: Figures 5a and 5b show the number of employed by age for regular workers and contingent workers, separately. We normalize the level in January 2020 to 100. For regular workers, changes during the first six months of the year are modest. For contingent workers, the decline by April 2020 is much larger in the range of 4 to 5% relative to the level in January 2020. Across age groups, changes from January 2020 to April 2020 are similar, but the decline from the first quarter to April and May of 2020 is larger for younger cohorts. Nonetheless, recovery is faster for younger cohorts in June as well. We discuss this heterogeneity in employment across age groups and employment types in more details in section 5.2.



(a) Regular Workers

(b) Contingent Workers

Figure 5: Changes in Employment by Age Group (Jan. 2020 = 100)

Note: Figure 5a shows the number employed by age for regular worker in each month between January and June 2020. Figure 5b shows the number of employed by age for contingent workers during the same period. The values in January 2020 are normalized to 100. Samples are restricted to workers aged 25 to 64. Series are not seasonally adjusted. The data is from Labor Force Survey (LFS) by the Ministry of Internal Affairs and Communications (MIC).

2.4 Changes in Earnings

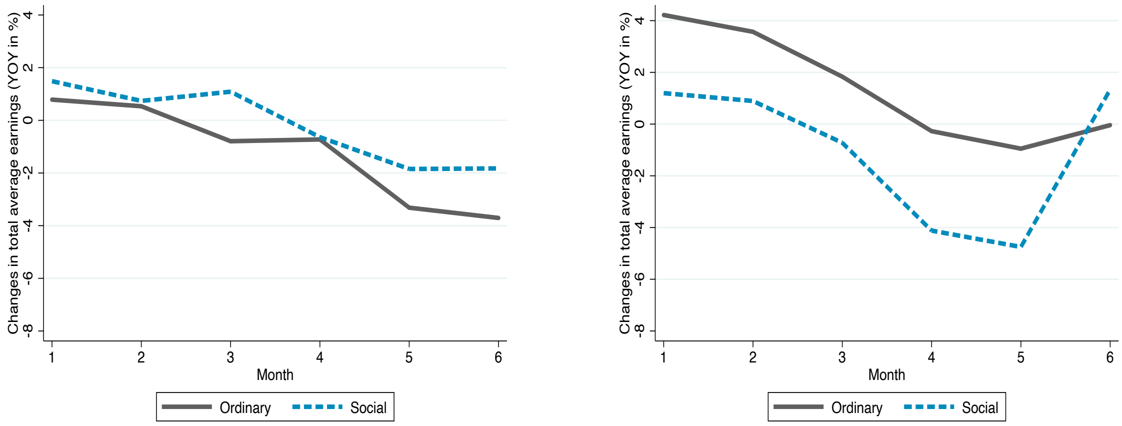
This section documents changes in earnings in Japan during the COVID-19 crisis, based on the MLS data. Figure 6 shows year-on-year changes in earnings in the ordinary and social sectors for regular workers and contingent workers, separately. Note that, in MLS, we use data for part-time workers as that for contingent workers due to data availability.[12]

As shown in Figure 6a, earnings of regular workers barely changed during the first quarter of 2020 compared to the same months of the previous year. The average earnings in both sectors declined in the second quarter of 2020, by 1 to 2% in the social sector compared to the same periods in 2019, and by 1 to 4% in the ordinary sector.

6b shows year-on-year changes in earnings for contingent workers in the first half of 2020 with significant differences in the changes across sectors. For workers in the social sector, earnings declined by 4 to 5% in April and May while those in ordinary sectors

[12]See section A for more details about the classification of employment types and 5.4.2 for further discussion on the difference in the classifications between the MLS and the LFS (or ESS) and its effects on the calibrated wage shocks.

experienced a relatively modest decline. There is a sharp rise in earnings of contingent workers in the social sector in June and a mild increase of those in the ordinary sector.[13]



(a) Regular Workers

(b) Contingent Workers

Figure 6: Changes in Earnings by Sector (in YOY change, %)

Note: Figure 6a and 6b show changes in fixed earnings by sector for regular and contingent workers (we use part-time workers), respectively. The values are in year-on-year change by monthly frequency, that is, they compare changes in earnings from the same month in the previous year. Series are not seasonally adjusted. The data is from the Monthly Labor Survey (MLS) by the Ministry of Health, Labour and Welfare (MHLW).

3 Model

Demographics: At age $j = 1$, individuals enter the economy with initial assets denoted as a_1. Individuals face probability s_j of surviving from age $j - 1$ to j. S_j denotes unconditional survival probability that an individual lives up to age j. We assume that they retire at the age of $j = J^R$ and live up to the maximum age of $j = J$. The deceased will be replaced by the newborn. Population is assumed to be constant and age distribution is stationary.

Endowment and Earnings: Individuals are born with gender $g = \{M, F\}$, male or female, and a skill type $s = \{H, L\}$, high or low. Upon entering the labor market, they are also assigned to an employment type $e = \{R, C\}$, regular or contingent, an occupation $o = \{o_1, o_2\}$, and sector $d = \{d_1, d_2\}$.

[13]The rise in the number of contingent workers in the social sector in June is driven by a recovery in earnings of retail, medical care and welfare and educational services industry, which offsets a continued decline in accommodation, eating and drinking services industries.

The two occupation types, o_1 and o_2, are associated with different levels of work flexibility, i.e. whether the job can be done remotely from home or not. The two sectors, $d = \{d_1, d_2\}$, produce different types of goods and services. Sector d_1 produces ordinary goods while sector d_2 produces social goods, which are more immune to infection risk in terms of consumption.

We let $x = \{j, g, s, e, o, d\}$ denote a state vector of each individual. We denote by μ_x the population share of individuals in state x, that is, age j, gender g, skill s, employment type e, occupation o, and sector d. Each individual's efficiency units of labor depend on the state vector x and are denoted as η_x, which varies over a life-cycle and approximates human capital that grows in age for each type of workers.

Earnings of an individual in state x at time t are given by

$$y_{x,t} = \lambda_{x,t}\eta_x w_t.$$

$\lambda_{x,t}$ summarizes shocks that affect earnings of type-x individuals at time t, which will be discussed in detail in section 5.2. w_t denotes the market wage per efficiency unit of labor.

Preferences: Individuals derive utility from consumption of two types of goods, c_1 and c_2, representing ordinary and social goods, respectively. We assume a period utility function:

$$U(c_1, c_2) = \xi_t \frac{\left[c_1^{\gamma_t} c_2^{1-\gamma_t}\right]^{1-\sigma}}{1-\sigma}, \tag{1}$$

where ξ_t represents an intertemporal preference shifter that affects marginal utility from consumption in each period. It is a weight on utility from consumption at time t relative to other times and may change with the arrival of the COVID-19 shocks, but it is assumed to be constant in normal times.

γ_t is a preference weight on ordinary goods, which, similarly to ξ_t, is constant in normal times, but may vary upon the arrival of the COVID-19. σ represents risk aversion. Individuals discount future utility at constant rate β.

There are no bequest motives and assets a_{t+1} left by the deceased are collected and transferred to all surviving individuals as accidental bequests, denoted as b_t, which satisfies the following equation.

$$b_t = \frac{\sum_x a_{t+1}(x)(1 - s_{j+1})\mu_x}{\sum_x \mu_x} \tag{2}$$

Government: The government operates a social security program, which provides a pension benefit p_t to each retiree. Individuals are taxed on their consumption, labor income and capital income at proportional rates, $\tau_{c,t}$, $\tau_{l,t}$, and $\tau_{a,t}$, respectively. We assume that the government budget is balanced each period and let a lump-sum transfer $\tau_{ls,t}$ absorb an imbalance from the period budget constraint (3).

$$\sum_{x}\left[\tau_{c,t}(c_{1,t}(x)+c_{2,t}(x))+\tau_{a,t}r_t(a_t(x)+b_t)+\tau_{l,t}\lambda_{x,t}\eta_x w_t\right]\mu_x=\sum_{x|j\geq j^R}p_t\mu_x+\sum_{x}\tau_{ls,t}\mu_x \tag{3}$$

Life-cycle Problem: The intertemporal preference ordering of an individual of type x born at time t is given by:

$$U(\{c_{1,t+j-1},c_{2,t+j-1}\}_{j=1}^{J})=\sum_{j=1}^{J}\beta^{j-1}S_j\xi_{t+j-1}\frac{\left[c_{1,t+j-1}^{\gamma_{t+j-1}}c_{2,t+j-1}^{1-\gamma_{t+j-1}}\right]^{1-\sigma}}{1-\sigma}$$

subject to:

$$\begin{aligned}(1+\tau_{c,t})(c_{1,t}+c_{2,t})+a_{t+1} &= (1-\tau_{l,t})\lambda_{x,t}\eta_x w_t+R_t(a_t+b_t)+\tau_{ls,t} \text{ for } j<j^R\\ (1+\tau_{c,t})(c_{1,t}+c_{2,t})+a_{t+1} &= p_t+R_t(a_t+b_t)+\tau_{ls,t} \text{ for } j\geq j^R\end{aligned}$$

where $R_t=1+(1-\tau_{a,t})r_t$ denotes net-of-tax gross interest rate at time t. We assume that the relative price of ordinary and social goods is constant and normalized to 1.

Initial Economy and Transition Dynamics The initial economy is stationary and characterized by demographics, $\{s_j\}_{j=1}^{J}$ and μ_x, type-specific labor productivity, η_x, a set of fiscal variables, $\{\tau_c,\tau_l,\tau_a,p\}$, factor prices, $\{r,w\}$, where individuals choose the optimal path of consumption and assets $\{c_1,c_2,a'\}$ at each age j. In equilibrium a lump-sum tax, τ_{ls}, balances the government budget (3) and the accidental bequest, b, satisfies the condition (2).

At time 1, we assume that individuals are hit by wage and employment shocks summarized in $\lambda_{x,t}$, which we will fully characterize in section 5.2, as well as by preference shocks, ξ_t and γ_t. Given the new paths of earnings and preferences, individuals re-optimize and choose a new path of consumption and assets. We let $\tau_{ls,t}$ adjust to balance the government budget to satisfy (3) in each period as well bequests b_t to meet the condition (2).

4 Calibration

This section describes parametrization of the economy presented above. The model frequency is quarterly. The initial economy approximates the Japanese economy prior to the onset of the COVID-19 shocks. We compute the transition dynamics starting in the first quarter of 2020, which corresponds to our initial economy. Parametrization of the initial economy is explained in this section and summarized in Table 1. The shocks that characterize the COVID-19 crisis are discussed in section 5.2.

4.1 Demographics

Individuals of the model enter the economy and start working at the age of 25, and they may live up to the maximum age of 100 years subject to age-specific survival probabilities s_j. The retirement age j^R is set at 65 years old. We calibrate the probabilities based on the estimates of the National Institute of Population and Social Security Research (IPSS) for the year 2020. We abstract from population growth and age distribution is stationary.

4.2 Preferences

The risk aversion parameter, σ, in the utility function (1) is set to 2.0. The parameter γ in the initial economy represents a weight on ordinary goods relative to social goods and it is set at 0.789 so the model matches the ratio of consumption expenditures of the two types of goods, based on the Family Income and Expenditure Share (FIES) from the Ministry of Internal Affairs and Communications (MIC). The parameter ξ that represents an intertemporal weight on consumption is set at 1 in the initial economy. In section 5.4, we simulate time-varying preference weights to approximate consumption data observed during the initial months of the COVID-19 crisis.

The subjective discount factor β is set at 1.0014 (or 1.0054 on an annual basis) to match the average growth of consumption between ages 25 and 50 as observed in the FIES data estimated in İmrohoroğlu et al. (2019).

4.3 Endowment and Human Capital

Each individual is endowed with a unit of time and supplies labor inelastically until they reach the retirement age j^R. The labor productivity $\eta_{j,g,s,e,o,d}$, which represents human capital of an individual worker and evolves over a life-cycle, is calibrated with the ESS data. Details about the categorization of individual workers into employment type, education level, industry and occupation are provided in appendix A.

We assume that the type of individual worker is determined upon entry to the labor market and fixed throughout their life-cycle. The share of each type is based on the distribution from the ESS data, and we take the average share of types among individuals aged between 30 and 59.

4.4 Government and Other Parameters

The pay-as-you-go social security program provides pension benefits p to each retiree. We assume that benefits are set to 30% of average earnings in the initial economy, based on the estimated replacement rate of social security benefits by the OECD.[14]

[14] OECD Pension at a Glance, 2020.

The consumption tax rate, τ_c, is set to 10%. Labor and capital income tax rates, τ_l and τ_a, are set to 13% and 20%, respectively, following İmrohoroğlu et al. (2019). The lump-sum transfer τ_{ls} is determined in equilibrium to absorb an imbalance from the government budget and is set to 7.3% of average earnings in the initial economy.

We set the interest rate at 2%, which is in the range of estimated returns to household saving, such as Aoki et al. (2016). Wage rate is normalized so that the average earnings in the initial economy is 1.

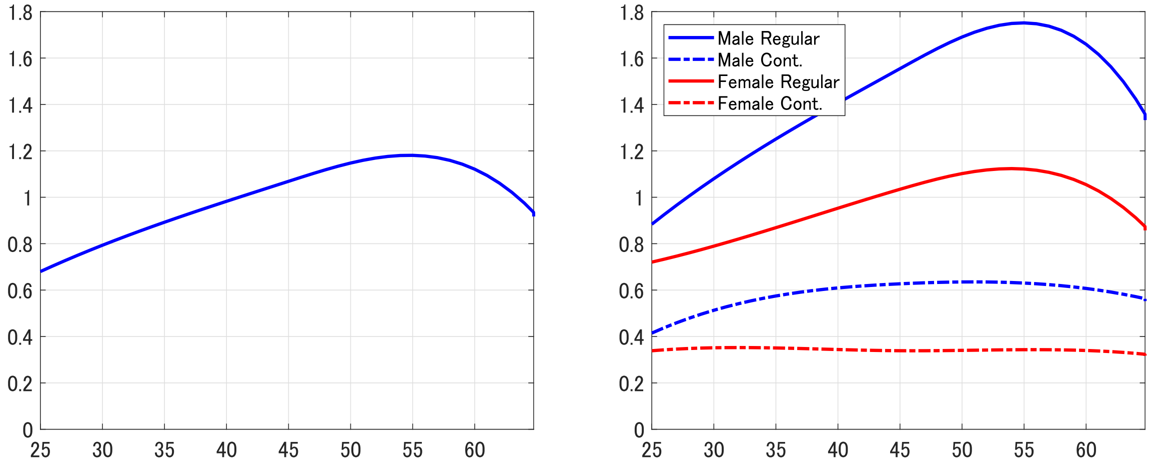
Table 1: Parameters of the Model: Initial Economy

Parameter	Description	Value
Demographics		
J^R	Retirement age	65 years
J	Maximum age	100 years
s_j	Survival probability	IPSS data
$\mu_{j,g,s,e,o,d}$	Population share	ESS data
Preference		
β	Subjective discount factor	1.0054 (annual)
σ	Risk aversion parameter	2.0
γ	Expenditure share on ordinary goods	0.789 (FIES)
ξ	Intertemporal weight	1 (before shock)
Human Capital		
$\eta_{j,g,s,e,o,d}$	Life-cycle human capital	ESS data
λ	Shocks to earnings	1 (before shock)
Government		
τ_c	Consumption tax rate	10%
τ_l	Labor income tax rate	13%
τ_a	Capital income tax rate	20%
τ_{ls}	Lump-sum tax/transfer	7.3% of avg. earn
p	Social security benefit	30% of avg. earn
Other Parameters		
r	Interest rate	2%
w	Wage rate	Normalization

5 Numerical Results

5.1 Baseline Model: Initial Economy

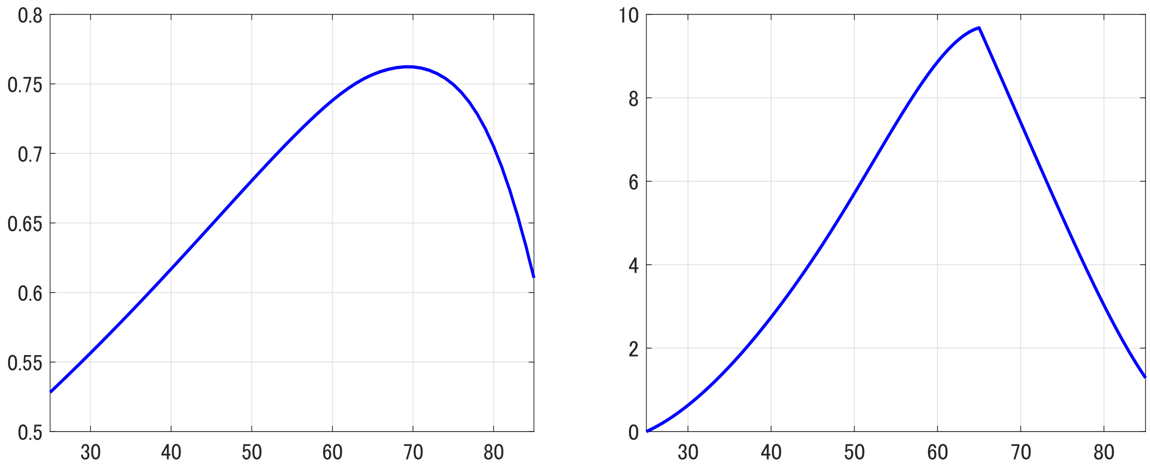
Figure 7 shows the earnings profile based on ESS data as discussed in section 4, for selected types of workers. The left panel shows average earnings of all workers at each age, normalized to the average earnings of all workers. It exhibits a hump-shaped profile, where earnings rise monotonically after the entry and peak at around age 55, when they start to decline. The right panel shows profiles for each gender and employment type and highlights a stark difference in earnings by individual characteristics.



(a) By Age (b) By Age, Gender and Emp. Type

Figure 7: Earnings in the Initial Economy (in model units; average earnings=1)

Solving the model described above, we obtain consumption and asset profiles of individuals averaged for each age, as shown in Figure 8.[15]



(a) Consumption by Age (b) Assets by Age

Figure 8: Consumption and Assets in the Initial Economy (in model units; average earnings=1)

[15]Note that assets are expressed in terms of average annual earnings, with an adjustment for quarterly frequency of the model.

5.2 The COVID-19 Shocks

We will next discuss the COVID-19 shocks that are introduced in the initial economy described above, before we study how they affect welfare of heterogeneous individuals in the model economy in section 5.3. This section revisits the data description presented in section 2 and explains how we process them as shocks that we feed into our model. We will decompose shocks into five; three associated with wage and employment shocks and two associated with preferences. Our main focus will be the first three. Table 2 summarizes five different types of shocks that we consider in the simulations.

Wage and Employment Shocks: Earnings of an individual in state x are hit by wage and employment shocks, summarized in $\lambda_{x,t} \equiv \omega_{e,d,t}\phi_{o,d,t}\nu_{j,e,t}$. This decomposition captures shocks to wages, $\omega_{e,d,t}$, and to employment, $\phi_{o,d,t}$ and $\nu_{j,e,t}$.

Wage shocks, $w_{e,d,t}$, are specific to the industry and vary by employment type, and they are measured as a change in earnings between the first and the second quarters of 2020, using the MLS data.[16] The shocks vary across the combination of employment type and industry, (e, d) = (1,1), (1,2), (2,1), (2,2), independently of other states of an individual, and are set to $\{w_{1,1}, w_{1,2}, w_{2,1}, w_{2,2}\} = \{0.9840, 0.9905, 0.9748, 0.9757\}$ based on the quarterly change in the data. Workers with contingent employment type experience a wage decline of 2.5% in the ordinary sector and 2.4% in the social sector, while the change is relatively small for those engaged in a regular job.

Employment shocks consist of two parts, employment type shock, $\nu_{j,e,t}$, and occupation-sector specific shock, $\phi_{o,d,t}$. We calculate the employment type shock, $\nu_{j,e,t}$, from a change in the number of employees between the first and the second quarters of 2020, using the LFS data.[17] Changes in employment by employment type vary by age, and we assume that the shock is age dependent. Figure 9 displays the decline in employment of contingent workers relative to regular workers. Contingent workers experienced a larger decline in employment across all age groups and Figure 9 shows that employment type shocks hit younger workers harder than older workers.

The finding that employment of contingent workers is more vulnerable to shocks is in line with observations during past recession episodes. We also note that it is in general difficult for firms to adjust the number of regular workers in a few months after the onset of the crisis and there is possibility that at least part of the difference in the employment adjustment between regular and contingent workers may be reflecting the speed that

[16]We use monthly MLS data since January 2013 to June 2020. Before calculating the shocks, we seasonally adjust raw data by converting data from monthly to quarterly frequency. Please see appendices A and B for detailed data structures and definitions.

[17]We use monthly LFS data since January 2013 to June 2020. Before calculating the shocks, we seasonally adjust raw data by converting data from monthly to quarterly frequency. Please see appendices A and B for detailed data structures and definitions.

different types of workers are affected by the crisis. It remains to be seen how employment of regular workers may be adjusted during the next quarters, especially if the shocks turn out to be very persistent.[18]

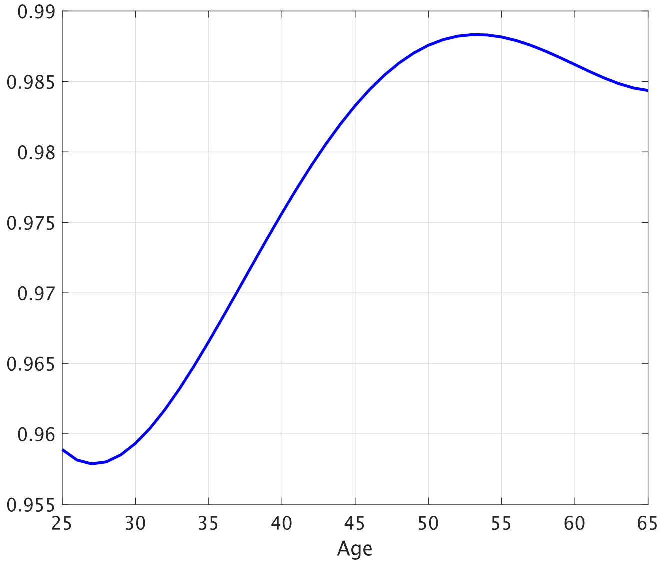


Figure 9: Employment-type Shocks by Age: Change in Employment of Contingent Workers relative to Regular Workers (Regular=1, 2020Q1 vs 2020Q2)

Note: This graph shows changes in the number of contingent workers relative to regular workers from age 25 to 65 between the first and second quarter of 2020. Series are seasonally adjusted. The data is from the Labor Force Survey (LFS) by the Ministry of Internal Affairs and Communications (MIC).

The occupation-sector specific employment shocks, $\phi_{o,d,t}$, are computed for each combination of (o, d) = (1,1), (1,2), (2,1), (2,2) and are set at $\{\phi_{1,1},\ \phi_{1,2},\ \phi_{2,1},\ \phi_{2,2}\} = \{0.9975,$ 1.0021, 0.9902, 0.9508$\}$. Employment of workers engaged in non-flexible occupations in the social sector is the most severely hurt, falling by 4.9%, while the change is relatively small for those in ordinary sector, or social but in the flexible occupation.[19, 20]

[18]We thank an anonymous referee for pointing out this possibility to us and suggesting that we state it explicitly.

[19]In computing the decline of employment by occupation and sector, we also use the LFS and ESS data of MIC. Since the LFS data only observe employment change of all type-(o, d) workers, shocks using only LFS may be biased by age-composition. Therefore, we use computed employment-age shocks $\nu_{j,e,t}$ and the ESS data to isolate shocks associated with industry and occupation in a way that is consistent with the aggregate changes in employment for each occupation and sector. More details of the computation are given in appendix B.

[20]Industries that contribute to a rise in the social and flexible group include educational support and schools.

Preference Shocks: Preference shocks are captured by share parameter shock, γ_t, and intertemporal preference shock, ξ_t.[21] The preference parameters are summarized in Table 2.

Figure 10 shows the expenditure share for social goods from the FIES data. Until the first quarter of 2020, the expenditure share of social goods remained stable at 21.1% on average, and it plummeted by 5.6 percentage points, to 15.5% in the second quarter of 2020. We take this decline in the expenditure share as reflected in the share parameter shock γ_t.

We calibrate intertemporal preference shock, ξ_t, to match the change in total expenditures from the fourth quarter of 2019 to the second quarter of 2020 by using the FIES, which stands at minus 6.3%. The value of ξ_t in the first quarter of the shock that generates a decline in consumption in the observed magnitude is 0.892.

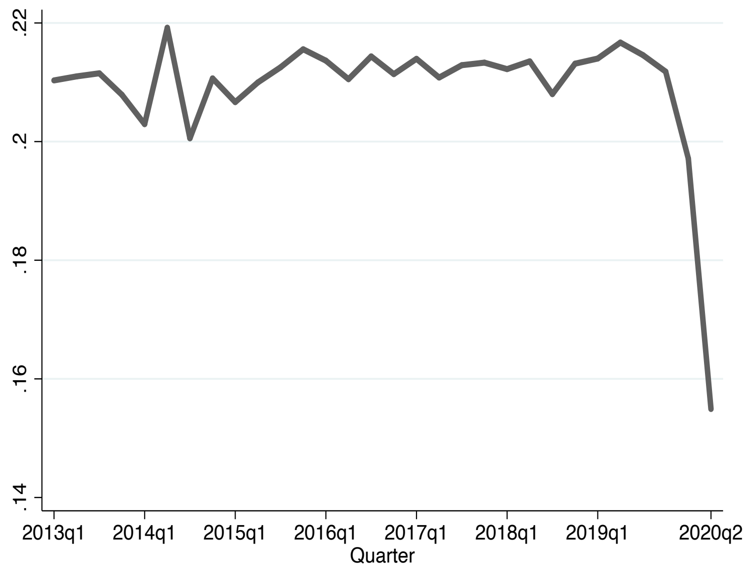


Figure 10: Expenditure Share of Social Goods

Note: This graph shows the expenditure share of social goods between the first quarter of 2013 and the second quarter of 2020. The samples are multiple-person households with no restriction of age. Data is constructed by monthly data from January 2013 to June 2020 by converting to quarterly data. Series are seasonally adjusted. The data is from the Family Income and Expenditure Survey (FIES) by the Ministry of Internal Affairs and Communications (MIC).

Table 2 summarizes the shocks observed during the first quarter of the COVID-19 crisis. As we stand, we do not know how long the shocks will remain after the second quarter of 2020. In the next section, we simulate the transition under some scenarios

[21] Similarly to wage and employment shocks, we use monthly consumption data, FIES, from January 2013 to June 2020 by converting to quarterly data and seasonally adjusting them. Please see appendices A and B for detailed data structure and definitions.

about the duration of the shocks.

Table 2: The COVID-19 Shocks in 2020Q2

Parameter	Description	Values, source
Wage Shocks		
$\omega_{e,d,t}$	Wage shock	$\{0.9840, 0.9905, 0.9748, 0.9757\}$, MLS
Employment Shocks		
$\nu_{j,e,t}$	Employment-age specific shock	Figure 9, LFS
$\phi_{o,d,t}$	Occupation-sector specific shock	$\{0.9975, 1.0021, 0.9902, 0.9508\}$, LFS and ESS
Preference Shocks		
γ_t	Share parameter shock	5.6ppt, FIES
ξ_t	Intertemporal preference shock	0.892, FIES

5.3 Transition Dynamics and Welfare Analysis

As discussed in section 5.2, COVID-19 brought sizable shocks to the labor market but the effects are far from uniform across heterogeneous groups of individuals. We now simulate the transition of our model economy assuming that individuals in the initial economy are hit by the shocks at time 1 and make a transition back to normal times over time.

In this section, we first focus on effects of labor market shocks through employment and wage shocks, explained in section 5.2. In the next section, we will also add shocks to preferences to account for changes in consumption shares and levels observed in the data. Our main focus, however, is on effects of heterogeneous labor market shocks on individuals' welfare.

As discussed above, it is very difficult, if not entirely impossible, to conjecture how long the shocks will persist. We assume that the shocks are temporary and disappear eventually, but will last for multiple periods. In the computation, we let the shocks diminish at rate ρ each period, with expected duration of $1/\rho$.

In the baseline scenario, we assume that shocks last for one year (four quarters) in expectation and set $\rho = 0.25$. In section 5.4, we also consider more and less optimistic scenarios, in which shocks diminish more quickly with expected duration of two quarters, and more slowly over six quarters, respectively.

Given the size of initial shocks as summarized in Table 2, the average earnings exhibit a decline of 2.5% in the first quarter of the crisis, which gradually diminishes over the following quarters, as shown in Figure 11. Note that the decline takes into account changes in both employment and earnings of individuals.

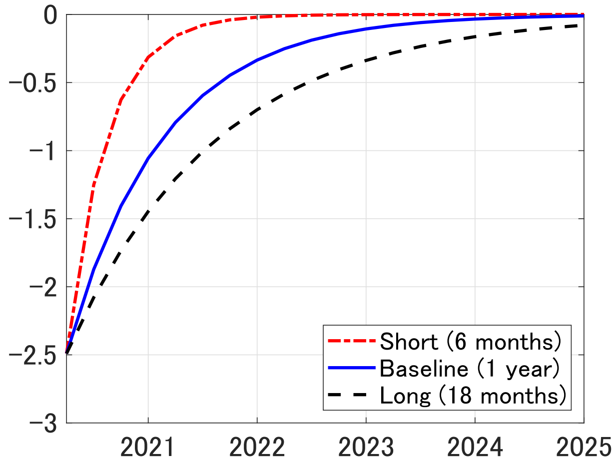
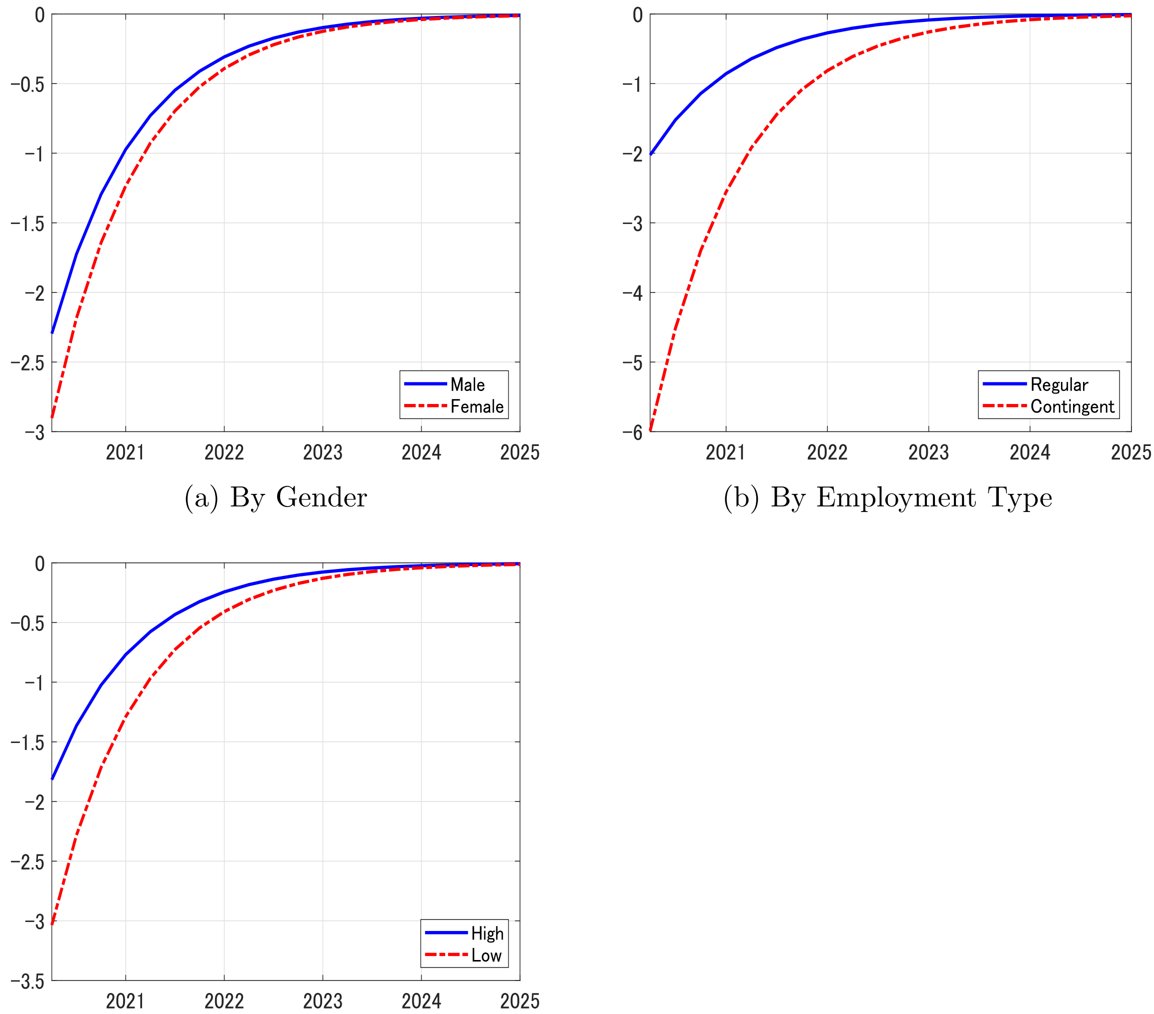


Figure 11: Changes in Average Earnings Relative to the Initial Economy (%)

The shocks, however, do not hit individuals equally. Figure 12 shows heterogeneity in the magnitude of shocks by gender, education level, and employment type under the baseline scenario where expected duration of shocks is four quarters. They are expressed as a percentage change in earnings of each type of worker relative to the levels in the initial economy.

As shown in Figure 12a, females on average experience a 2.9% drop in earnings while the decline is 2.3% for males. Figures 12b and 12c show an even starker difference in the decline of earnings across employment types and education levels of workers. Contingent workers experience a drop of 6.0% on average, while earnings of regular workers decline by 2.0%. Individuals with less than a college degree experience a sharper decline than those with a college degree. Note that we do not have any education-specific shock in the model and the difference comes from different compositions of workers within each group that are hit by the COVID-19 shocks.



(a) By Gender

(b) By Employment Type

(c) By Education

Figure 12: Changes in Average Earnings Relative to the Initial Economy (%)

We feed these shocks into our model in transition and compute welfare effects on different types of individuals. We use the initial economy as a basis of comparison and consider how individuals' welfare changes once the COVID-19 shocks hit the economy and they live through the new paths of earnings.

More precisely, we compute welfare of individuals under the initial economy as well as welfare of all types of individuals in an economy that experiences the COVID-19 shocks at time 1, which corresponds to the second quarter of 2020. We then compute consumption equivalent variation, "*CEV*," which equals a percentage change in consumption in the initial economy that would make an individual indifferent between living in the initial economy versus the economy facing COVID-19 shocks.

In order to account for difference in the expected duration of remaining life, which varies by individuals of different ages, we compute the present discounted value of consumption adjustment for the rest of an individual's life, which we call "*PV-CEV*," that will be needed to make the individual indifferent.[22]

Tables 3 and 4 show the *PV-CEV* of different groups of workers relative to average earnings of each group. Table 3 shows average welfare effects by gender, employment type and education level. Females on average face a welfare loss equivalent to 2.5% of their earnings, while the loss is more moderate at 1.8% for males. The table also shows a significant welfare loss for contingent workers, in a magnitude that corresponds to 4.6% and 5.1% of earnings for males and females, respectively.

Table 3: Welfare Effects by Gender, Employment Type and Education (aged 25-64, in PV-CEV)

		Emp. type		Education	
	All	Regular	Cont.	High	Low
All	−1.99	−1.60	−5.00	−1.44	−2.45
Male	−1.75	−1.64	−4.59	−1.39	−2.13
Female	−2.53	−1.46	−5.11	−1.62	−2.94

Table 4 shows welfare effects that differ across occupations and industries of individual workers. Workers in the social sector suffer significantly more from the COVID-19 crisis than those in the ordinary sector. The negative effect is much larger among those in non-flexible occupations, conditional on industry. Workers in the ordinary and flexible jobs experience a small loss of 1.6%, while those in the social and non-flexible jobs suffer from a large welfare loss of 4.9% relative to their earnings. Within each occupation and industry, females face a more significant welfare loss than males.

[22]Denoting the optimal consumptions of an individual in state x before the COVID-19 crisis by $\{c^*_{1,t}(x), c^*_{2,t}(x)\}$ and those in the economy hit by the COVID-19 shocks by $\{\widetilde{c}_{1,t}(x), \widetilde{c}_{2,t}(x)\}$, the *CEV* for an individual in state x and aged j at time t is computed as $\mu(x)$ that satisfies

$$\sum_{k=j}^{J} \beta^{k-j} U(c^*_{1,t+k-j}(x), c^*_{2,t+k-j}(x)) = \sum_{k=j}^{J} \beta^{k-j} U(\widetilde{c}_{1,t+k-j}(x)(1+\mu(x)), \widetilde{c}_{2,t+k-j}(x)(1+\mu(x))).$$

The *PV-CEV* for an individual in state x and aged j at time t is computed as

$$\overline{\mu}(x) = \sum_{k=j}^{J} \left[\prod_{i=j}^{k} s_i/R \right] /(s_j/R) \left(\widetilde{c}_{1,t+k-j}(x) + \widetilde{c}_{2,t+k-j}(x)\right) \mu(x).$$

Table 4: Welfare Effects by Gender, Industry and Occupation (aged 25-64, in PV-CEV)

	Ordinary		Social	
	Flexible	Non-flex.	Flexible	Non-flex.
All	−1.57	−2.32	−1.21	−4.86
Male	−1.42	−2.11	−0.81	−4.20
Female	−2.09	−3.73	−1.64	−6.00

We now turn our attention to heterogeneity in welfare effects across age groups. Figure 13 plots the welfare effects by gender and age in 2020. They are expressed in terms of $PV\text{-}CEV$ in units of average earnings of all workers, males, and females, respectively, in the initial economy. Retirees are not affected directly by the wage shocks but their welfare declines slightly as we assume that lump-sum transfers are adjusted to make up for a decline in tax revenues so the government can pay its social security expenditures. Since individuals approaching the retirement age suffer from a decline in earnings only for a small number of years, the loss is small relative to younger individuals. Among young individuals, the magnitude of welfare effects depends on the size of employment shocks that hit individuals of different age groups and the magnitude of lost earnings relative to their lifetime average earnings.

For females, the age-wage profile is relatively flat as shown in 7. Moreover, as we saw in Figure 9, employment of contingent workers is more severely hurt among the young, which adds to a larger welfare cost for them. The effects of shocks to contingent workers more clearly manifest among female workers, whose share of contingent workers is much larger than males. Females are also concentrated in the types of jobs that are more severely hit by the COVID-19 shocks and it contributes to a larger welfare loss than males. Among males, the age-wage profile is more hump-shaped than females and peaked at around 55. Males who are hit by the COVID-19 crisis at around these ages of high earnings suffer slightly more than younger males, which results in the mildly U-shaped welfare loss of male workers.

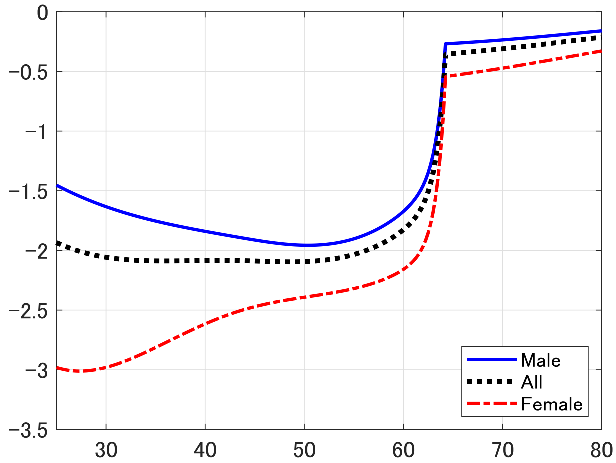
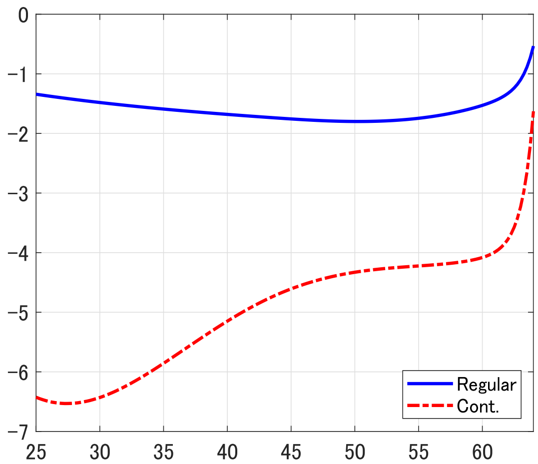
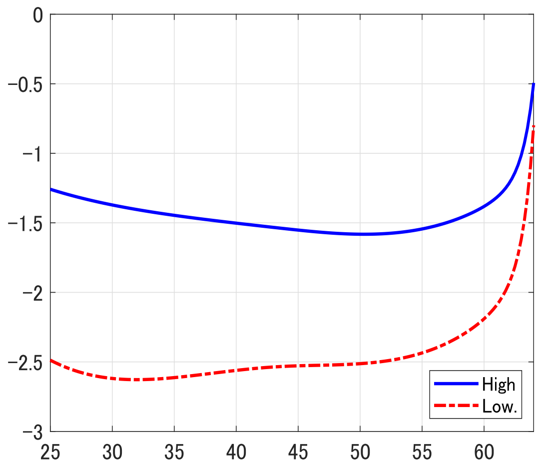


Figure 13: Welfare Effects by Age and Gender (in PV-CEV)

Figure 14 shows welfare effects by other dimensions of heterogeneity across workers. As shown in Figure 14a, contingent workers suffer more from the shocks than regular workers and the difference is larger among younger workers who are hit harder by the employment type shocks, as discussed in section 5.2. Figure 14b demonstrates that the low-skilled workers suffer by more than the high-skilled workers across all working ages.



(a) By Employment Type



(b) By Education

Figure 14: Welfare Effects by Age, Employment Type and Education (in PV-CEV)

The analysis reveals the fact that negative effects of the COVID-19 crisis in the labor market have very different implications for people of different age, gender, employment type, education and job type in terms of industry and occupation. In each dimension, the shock is larger for those who earn less initially.

Our model captures heterogeneity across workers in many dimensions that turn out to be critical in evaluating welfare effects the COVID-19 crisis in Japan. There are, however, other dimensions that are not captured in our model. For example, our model assumes full insurance within each group and does not account for within-type heterogeneity in other dimensions such as wealth, health status, family structure, etc, which presumably may be important dimensions to analyze once a model is properly extended and calibrated to data.

In the following section, we run a few additional experiments to consider alternative scenarios about duration of the COVID-19 shocks, and to introduce preference shocks to account for changes in consumption level and relative allocation across different types of goods. We will also consider welfare of some hypothetical households that consist of different types of individuals.

5.4 Sensitivity Analysis and Alternative Scenarios

5.4.1 Preference Shocks

We now consider shocks to preferences upon outbreak of the COVID-19 crisis. As summarized in section 5.2, there was a sizeable shift in the shares of consumption goods allocated to ordinary and social goods. The share of the latter was very stable at around 21% before the crisis and plummeted to 15.5% in the second quarter of 2020. At the same time, when we compare the level between the fourth quarter of 2019 and the second quarter of 2020, we found the average consumption level also fell by 6.3%.[23] We adjust preference parameters ξ_t and γ_t so that the model approximates these changes in consumption shares and average levels observed in the data. Similarly to the shocks to the labor market considered in section 5.3, we assume that the shocks will last for one year on average and diminish at rate $\rho = 0.25$.

Table 5 shows welfare effects from the transition incorporating preference shocks. With preference shocks, quantifying welfare effects of the COVID-19 becomes challenging since a new set of preference parameters directly affects welfare. Therefore, we compute welfare effects from different paths of consumption before and after the COVID-19 shocks, evaluated in terms of utility function in the initial economy. Although the level of welfare

[23] We approximate the effect of the COVID-19 shocks on the consumption level by a change between the fourth quarter of 2019 and the second quarter of 2020, rather than between the first and second quarters of 2020. We note some caution in quantifying the impact of COVID-19 on consumption from the time series data over this short time horizon before and after the crisis. Some decline in consumption had already begun in the latter half of the first quarter of 2020, in March in particular, and we avoid using this quarter as a basis of comparison. Also, there was a hike in the consumption tax rate from 8% to 10% in October 2019. The government implemented tax credits under some conditions for purchases until June 2020, in order to alleviate negative effects on consumption caused by the tax increase and to encourage more "cashless" transactions. Isolating pure effects of the COVID-19 crisis on consumption from these and other factors would be a non-trivial task. For these reasons, we use a quarterly change in consumption from 2019Q4 to 2020Q2 as approximating the COVID-19 shocks. Although the estimated change may vary under alternative assumptions, we think the main message from the welfare comparison across heterogeneous individuals presented in this section would remain intact.

effects requires caution in interpretation, we confirm the same pattern of heterogeneous impact across different types of individuals, as shown in Table 5.[24] Welfare effects are more negative for females than males, contingent workers are hit harder than regular workers and so are the low-educated than the high-skilled.

Table 5: Welfare Effects with Preference Shocks (aged 25-64, in PV-CEV)

		Emp. type		Education	
	All	Regular	Cont.	High	Low
All	−1.11	−0.80	−3.49	−0.65	−1.49
Male	−0.96	−0.87	−3.49	−0.64	−1.31
Female	−1.44	−0.59	−3.49	−0.72	−1.77

5.4.2 Employment Type Definitions

As discussed in section 2.2 and in more details in appendix A, there is some discrepancy in the definition of "contingent" workers between the MLS and the LFS or ESS. In the LFS, the employment type is based on how workers are called by employers and it is classified similarly in the ESS. The MLS does not have an equivalent category and we use earnings of "part-time" workers, as representing that of contingent workers in the model. Part-time workers are defined as those who work either fewer hours per day or fewer days than regular workers.

Since the classification of the LFS/ESS is not based on work hours, we may include workers categorized as "full-time" in the MLS that are grouped as contingent workers in the LFS/ESS as well as "part-time" workers in the MLS that are grouped as regular workers in the LFS/ESS. The fraction of the latter, i.e. the number of regular workers in the LFS/ESS who work fewer hours as "part-time" workers in the MLS is very small at a few percentage of all regular workers in the 2017 data. Hence, the difference in the distribution of employment types in the two databases is mostly attributable to the former.

Table 6 below shows fractions of regular workers in the MLS, LFS and ESS for workers aged 15 and above. The last two columns, fractions of regular workers in the LFS and ESS, demonstrate that the classification is close in the two.

[24] Although the focus of the analysis is a relative difference of welfare effects across different types of individuals, the levels of welfare effects also differ from those in the baseline without preference shocks since we are imposing the same pre-crisis preference in the computation. For example, shocks to the share parameter induce more consumption of ordinary goods, which carry more weight in the pre-crisis preference and make the welfare effects less negative (i.e. closer to zero), compared to the welfare effects evaluated without preference shocks. Other equilibrium effects also affect the magnitude of the welfare evaluated under the pre-crisis preference. We note, however, that since preferences are not type-specific, these effects do not affect our relative comparison of welfare across different types of individuals.

Table 6: Fractions of Regular Workers (aged 15 and above, in %, 2017)

	MLS	LFS	ESS
All	76.5	65.2	64.5
Male	86.3	80.1	80.0
Female	67.3	46.6	45.6

The fraction of regular workers is larger in the MLS than in the LFS/ESS. The difference is particularly large for females, implying that there are many female workers, called contingent workers by employers, who work as many hours as regular workers. By assuming the (more negative) earnings shocks of "part-time" workers for these workers, we could over-estimate the shocks to regular workers in the simulations.

In order to assess such effects on wage shocks calibrated from the MLS data, we compute wage shocks $\omega_{e,d,t}$ assuming that part of contingent workers, corresponding to the difference between the fractions in the MLS and the LFS shown in Table 6, are in fact regular workers of the MLS, and include them carrying the wage shocks of regular workers instead of contingent workers.

As a result, wage shocks of contingent workers change from 0.9748 to 0.9796 for the ordinary sector and from 0.9757 to 0.9802 for the social sector. Since the shocks to "full-time" workers are milder than those to "part-time" workers, the shocks of contingent workers would become milder.

Table 7 shows welfare effects of the COVID-19 shocks under an alternative specification of wage shocks, adjusted for the discrepancy in the distribution of employment types between the MLS and LFS/ESS as described above. Compared to the baseline results in Table 3, negative welfare effects on contingent workers are slightly mitigated, increasing from -5.0% to -4.0% for both males and females, for example, although main results remain unchanged.

Table 7: Welfare Effects under Alternative Wage Shocks (aged 25-64, in PV-CEV)

		Emp. type	
	All	Regular	Cont.
All	-1.95	-1.59	-4.69
Male	-1.73	-1.64	-4.29
Female	-2.43	-1.45	-4.79

5.4.3 Duration of Shocks

In the baseline simulations, we assume that the COVID-19 shocks will diminish at rate $\rho = 0.25$ on a quarterly basis and last for 4 quarters in expectation. We consider two alternative scenarios in which shocks last for 2 and 6 quarters on average. Table 8 shows how welfare effects vary by duration of the shocks in the labor market. Not surprisingly, welfare loss is magnified when shocks last longer and exacerbate welfare loss of the vulnerable more. The table shows the difference across genders, but the pattern of heterogeneous welfare effects across other dimensions remains the same as in the baseline simulations presented above.[25]

Table 8: Welfare Effects and Shock Durations (aged 25-64, in PV-CEV)

Duration	6 months	Baseline 12 months	18 months
All	−1.01	−1.99	−2.94
Male	−0.89	−1.75	−2.58
Female	−1.29	−2.53	−3.72

5.4.4 Welfare Effects across Household Types

The unit of our analysis is an individual, and we do not explicitly consider a family structure in the baseline simulations. We observed a significant difference in the labor market experience across individuals by their characteristics. An especially large difference was observed between regular and contingent workers.

In this section, we simulate a model to infer how a household that consists of two earners of particular types may fare against other types of married households. We hypothetically construct earnings of a typical male and female individual engaged in a regular or contingent job. Four types of households that differ by gender and employment type of spouses are constructed. We then quantify welfare effects of the COVID-19 shocks on these four types of households and compare them.

Figure 15 shows the welfare effects married individuals in terms of *PV-CEV*, present discounted value of consumption equivalent variation, for each individual in a two-earner household of different combinations of spouses' employment type. As in previous figures, they are expressed in terms of average earnings of each type of households in the initial economy. Not surprisingly, members of two-earner households that consist of two contingent workers suffer the most. The negative effect of the COVID-19 is the smallest for married households with two regular workers.

[25]We do not show all the results under alternative duration assumptions due to a space constraint, but they are available from the authors upon request.

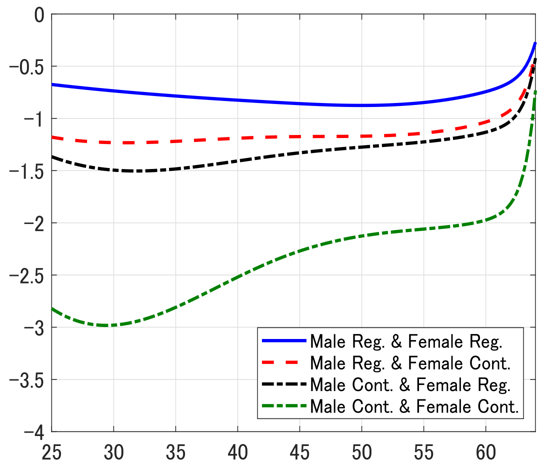


Figure 15: Welfare Effects of Married Individuals by Family Type (in PV-CEV)

Our model assumes exogenous labor supply and also abstracts from home production, which potentially would be an important factor, since how the COVID-19 shocks affect allocations of time endowment, especially within a household may have important welfare implications. Not only an increase in unemployment, but also a rise in the amount of remote work most likely increases total time spent at home and the demand for home production. Moreover, the need to take care of children during the school closure period increases a demand for hours spent at home and affects households with children and labor supply of working parents.

The reallocation of productions in the market and at home also affects the evaluation of effects on the aggregate economy. Leukhina and Yu (2020) examined changes in time allocations of households during the COVID-19 recession using the American Time Use Survey. They estimate that the monthly value of home production after the COVID-19 crisis rose by the amount equivalent to more than 10% of a decline in the monthly GDP. Alon et al. (2020b) also argue that increased childcare needs at home contribute to a rise in unemployment of females. Although it goes beyond the scope of the paper to fully incorporate these factors, we note how the COVID-19 crisis affected time allocation of individuals in different types of households is an important research theme for future.

6 Conclusion

In this paper, we document heterogeneous responses in employment and earnings to the COVID-19 shocks during the initial months after the onset of the crisis in Japan. We then feed these changes in the labor market into a life-cycle model and evaluate welfare consequences of the COVID-19 shocks across heterogeneous groups of individuals.

We find that negative effects of the COVID-19 shocks in the labor market significantly vary across people of different age group, gender, employment type, education level, industry and occupation. In each dimension, the shock is amplified for those who earn less prior to the crisis. Contingent workers are hit harder than regular workers, younger workers than older workers, females than males, workers engaged in social and non-flexible jobs than those in ordinary and flexible jobs. Our study identifies groups of individuals that are more severely hurt than others from the COVID-19 crisis, and suggests how the policy could be structured, which aims to reach the most vulnerable and the most severely affected.

Although the scope of the paper is to evaluate short-run impacts of COVID-19 in the labor market during the initial months of the crisis, there may well be other effects triggered by the crisis, such as structural changes in the labor market over the medium and long-run. Such changes may also depend on how long various shocks we observe at this moment will persist and whether they will be repeated multiple times. These topics, which cover a longer time horizon, are left for future research.

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A Data Appendix

A.1 Labor Force Survey (LFS)

Sample: The Labor Force Survey (LFS) is a cross-sectional household survey conducted by the Ministry of Internal Affairs and Communications (MIC). The LFS is established to elucidate the current state of employment and unemployment in Japan. The survey was first conducted in July 1947. For our research propose, we use the monthly data, known as the "Basic Tabulation," for the period from January 2013 to June 2020. The survey unit is a household residing in Japan, excluding foreign diplomatic and consular corps, their family members, and foreign military personal and their family members. For the "Basic Tabulation," approximately 40 thousand households are selected. The questions on employment status are asked to only members aged 15 years or over. The LFS is conducted as of the last day of each month (except for December), and the employment status is surveyed for the week ending the last day of month.[26]

Definition of Variables: Employment status of the population aged 15 years and above is classified according to activity during the reference week. Our interest is the number of employed persons among the population aged 15 years and above, especially aged 25 to 64. Employed persons consist of the employed at work and the employed not at work. Employed persons at work are defined as all persons who worked for (1) pay or profit, or (2) worked as unpaid family workers for at least one hour. Thus, LFS does not include people with jobs but not at work as employed at work. For example, those who did not work but received or were expected to receive wages or salary are classified as an employed person not at work.

Employed people also consist of employees, self-employed worker, and family workers according to their main job. We use employees (those who work for wages or salaries) and

[26] More detailed information can be found here: https://www.stat.go.jp/english/data/roudou/pdf/1.pdf

classify them as regular or contingent (non-regular) based on what they are termed by their employers. The regular employment type includes executives of companies or corporations and regular staff who are termed "regular (*seiki*) employees." The contingent (*hiseiki*) employment type includes part-time workers, albeit (temporary workers), dispatched workers from a temporary labor agency, contract employees, entrusted employees, and others.

Industry classification follows the basis of the Japan Standard Industrial Classification (JSIC) according to the main types of business and industries of establishments, as revised in October 2013. We allocate industries into two sectors, which we call ordinary and social sectors.

Occupations are classified based on the Japan Standard Occupational Classification (JSOC), as revised in December 2009. We allocate them into two occupations, which we call flexible and non-flexible occupations.

Note that the samples of both industry and occupation are all workers aged 15 to 64, including not only employees (regular and contingent workers) but also other types of workers (self-employed worker and family workers), since more granular age and employment type categories cannot be obtained from publicly available aggregate data.

A.2 Monthly Labor Survey (MLS)

Sample: The Monthly Labor Survey (MLS) is a cross-sectional monthly survey conducted by the Ministry of Health, Labour and Welfare (MHLW). The MLS is established to measure changes in employment, earnings, and hours worked on both national and prefectural levels. The survey was first conducted in July 1923. For our research propose, we use the monthly national data for the period from January 2013 to June 2020. The MLS was conducted on approximately 33 thousands establishments, selected from all private and public sector establishments normally employing five or more regular employees and belonging to 16 categorized sectors. Surveys are conducted monthly and use values as of the end of each month.[27]

Definition of Variables: In this paper, we use the monthly data for contractual cash earnings of regular employees. The regular employees are defined as workers who satisfy condition (1) those who are employed for an indefinite period of time, or (2) those employed for a fixed term of one month or more. Then, the regular employees are classified as "full-time employees" and "part-time workers." In section 5, we follow this definition as employment type. The part-time workers are those who satisfy condition (1) whose scheduled working hours per day are shorter than ordinary workers, or (2) whose

[27] More detailed information can be found here: https://www.mhlw.go.jp/english/database/db-slms/dl/slms-01.pdf

scheduled working hours per day are the same as ordinary workers, but whose number of scheduled working days per week is fewer than ordinary workers.

The 16 industry categories follow the basis of the JSIC according to the main types of business and industry of establishments, as revised in October 2013. The 16 industry categories are a slightly less granular categorization than that of the LFS. Then we similarly allocate industry into two categories, which we call ordinary and social by following the strategy taken in Kaplan et al. (2020b).

- Ordinary Sector: mining and quarrying of stone and gravel; electricity, gas, heat supply and water; construction; manufacturing; wholesale; transport and postal service; information and communications; finance and insurance; real estate, goods rental and leasing.

- Social Sector: retail trade; education and learning support; medical, health care and welfare; living related, personal, and amusement service; accommodations, eating and drinking places; scientific research, professional and technical services; compound services; services, n.e.c.

We use as earnings contractual cash earnings plus bonuses in this paper. Cash earnings are the amount before deducting taxes, social insurance premiums, trade union dues or purchase price, etc. Contractual cash earnings are defined as earnings paid according to a method and conditions previously determined by labor contract, collective agreement, or wage regulations of establishments. The contractual cash earnings consist of scheduled cash earnings and non-scheduled cash earnings, which are overtime pay. Overtime pay is the wages paid for work performed outside scheduled working hours, such as at night and in the early morning. Note that contractual cash earnings include a salary paid without actual labor, such as leave pay.

A.3 Employment Status Survey (ESS)

Sample: The Employment Status Survey (ESS) is a cross-sectional household survey conducted by the Ministry of Internal Affairs and Communications (MIC). The ESS aims to obtain basic data on actual conditions of the employment structure at both national and regional levels by surveying the usual labor force status in Japan. The ESS was conducted every three years between 1956 and 1982, and has been conducted every five years since 1982. For our research propose, we use the latest data collected in October 2017. The survey unit is a household of members aged 15 years and above residing in Japan except for (1) foreign diplomatic corps or consular staff (including their suite and their family members), (2) foreign military personnel or civilians (including their family members), (3) persons dwelling in camps or ships of the Self-Defense Forces, (4) persons serving sentences in prisons or detention houses, and (5) inmates of reformatory institutions or women's guidance homes. Approximately 490 thousand households living in sampled units are selected.[28]

Definition of Variables: To obtain the distribution of employees with various characteristics, we use the "order-made" data and focus on employees aged 20 and over. For characteristics of employees, we follow the information about age, gender, education, employment type, sector, occupation, and income.

Age is counted as of September 30, 2017. In this paper, we use data for the 10-year age groups: 30s, 40s and 50s. Education status is defined according to the information on the survey date. In this paper, we allocate education status into two types, which we call high and low. We define employees as high-skilled if they have a college or higher degree, and low skilled otherwise.

In this paper, we focus on employees and classify them into two types of employment: regular and contingent. The regular employment type includes executives of companies or corporations and regular staff who are termed "regular (*seiki*) employees." The contingent (*hiseiki*) employment type includes part-time workers, albeit (temporary workers), dispatched workers from a temporary labor agency, contract employees, entrusted employees, and others.

Industry classification follows the basis of the JSIC for the main types of business and industries of establishments, as revised in October 2013. We allocate industries into two sectors, which we call ordinary and social sectors.[29]

Occupations are classified based on the JSOC, as revised in December 2009. We allocate them into two groups, which we call flexible and non-flexible occupations.

Income is defined as the sum of annual income from October 2016 to September 2017 that workers earn from their main jobs excluding non-monetary income. Note that the income of those who changed their jobs or took up a new job during the past year is calculated based on income from the day when they start a new job up to the reference day assuming that they keep working for a year. The income of employees is gross earnings inclusive of tax gained during the past year from wages, salaries, charges for

[28] More detailed information can be found here: `https://www.stat.go.jp/english/data/shugyou/2017/outline.html`

[29] As discussed in the paper, we follow the classification of Kaplan et al. (2020b), but our classification in the ESS based on the JSIC does not exactly match their classification based on the NAICS. We include the industry group called "academic research, professional and technical services" (Major Category "L" under the industrial classification of the ESS) to the social industry. This group has an overlap with "Professional and business services" of Kaplan et al. (2020b), which they classify in the ordinary sector. This group, however, also includes some industries that Kaplan et al. (2020b) classify in the social sector, such as advertisement, art and photography, and there are other service industries that involve face-to-face elements such as construction services, and product inspections. One could alternatively classify part of this group in the ordinary sector and we conjecture it will not significantly affect our quantitative analysis and main results.

labor, various allowances, bonuses, and the like. Incomes are grouped into 17 categories: less than 50, 50-99, 100-149, 150-199, 200-249, 250-299, 300-399, 400-499, 500-599, 600-699, 700-799, 800-899, 900-999, 1000-1249, 1250-1499, over 1500 (in 10 thousand yen). When we calculate average income, we use the middle value of income categories for all categories but the smallest and largest groups. For the group with less than 50, we use 25, and for the group with over 1500, we use 1500.

A.4 Family Income and Expenditure Survey (FIES)

Sample: The Family Income and Expenditure Survey (FIES) is a cross-sectional household survey conducted by the Ministry of Internal Affairs and Communications (MIC). The survey was first conducted in September 1950. For our research propose, we use the "Monthly Report on the Family Income and Expenditure Survey" of two-or-more-person households (multiple-person households) for the period from January 2013 to June 2020. The survey unit is a household residing in Japan, except for (1) one-person student households, (2) inpatients in hospitals, inmates of reformatory institutions, etc., (3) households which manage restaurants, hotels, boarding houses, or dormitories, sharing their dwellings, (4) households which serve meals to boarders even though not managing boarding houses as an occupation, (5) households with 4 or more live-in employees, (6) households whose heads are absent for a long time (three months or more), (7) foreigner households. The entire land of Japan is stratified into 168 strata. Approximately 8,000 multiple-person households and 750 one-person households are surveyed every month from the strata. Multiple-person households are surveyed for six consecutive months, while one-person households are surveyed for three consecutive months, but only after 2002.[30]

Definition of Variables: In this paper, we use monthly multiple-person household's income and expenditure data. We allocate commodities into two types from two different sectors, which we call ordinary and social sectors, and closely follow the strategy taken in Kaplan et al. (2020b).

- <u>Ordinary Sector:</u> food except for meals outside the home; housing except for service charges for repairs and maintenance; fuel, light and water charges; furniture and household utensils except for domestic service; clothing and footwear except for services related clothing; medical care except for medical service; transportation and communication; school text books and reference books for study; culture and recreation except for recreational services; other consumption expenditures except for personal care services.

[30]More detailed information can be found here: https://www.stat.go.jp/english/data/kakei/1560.html

- Social Sector: meals out side the home, service charges for repairs and maintenance, domestic service, services related to clothing, medical service, school fees, tutorial fees, recreational service, personal care services.

B Calibration of Shocks

Seasonal Adjustment and Conversion of Frequency: As discussed in appendix A, we use the monthly labor and consumption data to calculate the shocks, which we feed into the model. The frequency of our model, however, is quarterly, and we use changes between the first quarter and the second quarter of 2020 as the COVID-19 shocks. For the purpose of the calibration in section 5.2, we convert monthly data into quarterly data and seasonally adjust it by using X12 ARIMA.[31]

Occupation-sector specific shocks: The occupation-sector specific shock $\phi_{o,d,t}$ is one of the two employment shocks and this shock hits workers of each combination of occupation and sector (o, d) = (1,1), (1,2), (2,1), (2,2), independently of the other individual characteristics.

We first compute changes in employment between the first and the second quarters of 2020 for each combination. Note that the LFS's aggregate data only provide changes in employment of "all" type-(o, d) workers and do not represent pure (o, d) shocks associated with occupation and sector.[32] If, for example, social and non-flexible workers are disproportionately contingent, their employment may decline sharply, not because of the (o, d) shock, but because of the employment-type shock. Thus, we use the employment-age shock $\nu_{j,e}$ by the LFS and, the distribution $\mu_{j,e|o,d}$ over employment type and age, conditionally on (o, d) by ESS. Note $\sum_{j,e} \mu_{j,e|o,d} = 1$. Denoting the employment changes of all type-(o, d) workers as $x_{o,d}$, we calculate the occupation-sector specific shocks $\phi_{o,d}$ so that they satisfy

$$\phi_{o,d} = \sum_{j,e} \mu_{j,e|o,d}(1 - \nu_{j,e})x_{o,d}$$

for each combination of (o, d).

[31] We use the R package "x12". https://cran.r-project.org/web/packages/x12/x12.pdf

[32] Note that the samples of both occupations and sectors are all workers aged 15 to 64, including not only employees (regular and contingent workers) but also other types of workers such as the self-employed, since more granular age and employment type categories cannot be obtained from publicly available aggregate data. Then, we restrict the samples, 10-year age groups, from 20s to 60s for ESS and LFS of both employment and age.

C Computation Algorithm

This appendix describes computation of equilibrium of our model. First, we compute an equilibrium of the initial economy and second, the transition from the initial economy to the final economy. The final economy is assumed to be the same as the initial economy and effects of the shocks disappear in the long-run. The transition dynamics are computed in the following three steps. We assume that the transition takes T periods, which is long enough so that the economy converges to the final economy smoothly.

1. Guess the paths of two equilibrium objects, $\{\tau_{ls,t}, b_t\}_{t=1}^{T}$; lump-sum taxes and bequests.

2. Solve individuals' problems. See below for details.

3. Check if the government budget constraint is satisfied. If not, adjust $\tau_{ls,t}$. Check if assets of the deceased equal accidental bequests. If not, adjust b_t. Continue until the conditions are satisfied for all $t = 1, ...T$.

The equilibrium of the initial economy is computed in similar steps, with only one time period and by setting $T = 1$.

Individuals' Life-cycle Problem: We now describe individuals' life-cycle problem and details of step 2 above. Recall the utility function

$$U(c_{1,t}, c_{2,t}) = \xi_t \frac{\left[c_{1,t}^{\gamma_t} c_{2,t}^{1-\gamma_t}\right]^{1-\sigma}}{1-\sigma} \tag{4}$$

where $c_{1,t}$ and $c_{2,t}$ denotes an individual's consumption of ordinary and social goods by individual at time t. Recall also the budget constraint

$$(1 + \tau_{c,t})(c_{1,t} + c_{2,t}) + a_{t+1} = y_{x,t} + R_t(a_t + b_t) + \tau_{ls,t} \tag{5}$$

where $y_{x,t}$ denotes after-tax earnings of an individual of a working age in state x or pension benefits in case of a retiree.

From an intratemporal condition

$$c_{2,t} = \frac{1-\gamma_t}{\gamma_t} c_{1,t} \equiv \Lambda_t c_{1,t} \tag{6}$$

where

$$\Lambda_t \equiv \frac{1-\gamma_t}{\gamma_t}.$$

Plug (6) in (4),

$$U(c_{1,t}, c_{2,t}) = \xi_t \frac{\left[c_{1,t}^{\gamma_t} \left(\Lambda_t c_{1,t}\right)^{1-\gamma_t}\right]^{1-\sigma}}{1-\sigma} = \Omega_t \frac{c_{1,t}^{1-\sigma}}{1-\sigma} \equiv u(c_{1,t}) \tag{7}$$

where

$$\Omega_t \equiv \xi_t \Lambda_t^{(1-\gamma_t)(1-\sigma)}$$

Now consider an intertemporal decision of individuals. Plug (6) in (5),

$$(1+\tau_c)\frac{1}{\gamma_t}c_{1,t} + a_{t+1} = y_{x,t} + R_t(a_t + b_t) + \tau_{ls,t} \tag{8}$$

Rewrite an individual's life-cycle problem in terms of $c_{1,t}$ as

$$\max \sum_{j=1}^{J} \beta^{j-1} \left(\prod_{k=1}^{j} s_k \right) u(c_{1,j,t})$$

where $u(c_{1,t})$ is defined as in (7) subject to (8).

From the Euler equation

$$\frac{c_{1,t+1}}{c_{1,t}} = \left(\beta s_{j+1} R_{t+1} \frac{\Omega_{t+1}}{\Omega_t} \frac{\gamma_{t+1}}{\gamma_t} \right)^{\frac{1}{\sigma}} \equiv g_{1,t+1}^c$$

where $g_{1,t+1}^c$ denotes gross growth rate of consumption of goods 1 between time t and $t+1$.

Consumption of goods 2 is given as (6), and we have

$$\frac{c_{2,t+1}}{c_{2,t}} = \frac{\Lambda_{t+1} c_{1,t+1}}{\Lambda_t c_{1,t}} = \frac{\Lambda_{t+1}}{\Lambda_t} g_{1,t+1}^c \equiv g_{2,t+1}^c$$

Consumption of goods 1 and goods 2 of an individual aged j born in time t is

$$c_{1,t+j-1} = c_{1,t} \prod_{k=1}^{j} g_{1,t+k-1}^c \tag{9}$$

$$c_{2,t+j-1} = c_{2,t} \prod_{k=1}^{j} g_{2,t+k-1}^c \tag{10}$$

where $g_{1,t}^c = g_{2,t}^c = 1$.

Present discounted values of expenditures for consumption goods 1 and 2, $C_{1,t}$ and $C_{2,t}$, for an individual born at time t, are given as

$$\begin{aligned}
C_{1,t} &= c_{1,t} + \sum_{j=2}^{J} \left(\prod_{k=2}^{j} \frac{s_k}{R_{t+k-1}} \right) c_{1,t+j-1} \\
&= c_{1,t} \left[1 + \sum_{j=2}^{J} \left(\prod_{k=2}^{j} \frac{s_k}{R_{t+k-1}} \right) \left(\prod_{k=1}^{j} g_{1,t+k-1}^c \right) \right] \\
C_{2,t} &= c_{2,t} + \sum_{j=2}^{J} \left(\prod_{k=2}^{j} \frac{s_k}{R_{t+k-1}} \right) c_{2,t+j-1} \\
&= c_{2,t} \left[1 + \sum_{j=2}^{J} \left(\prod_{k=2}^{j} \frac{s_k}{R_{t+k-1}} \right) \left(\prod_{k=1}^{j} g_{2,t+k-1}^c \right) \right] \\
&= c_{1,t} \frac{1-\gamma_t}{\gamma_t} \left[1 + \sum_{j=2}^{J} \left(\prod_{k=2}^{j} \frac{s_k}{R_{t+k-1}} \right) \left(\prod_{k=1}^{j} g_{2,t+k-1}^c \right) \right]
\end{aligned}$$

Define $\tilde{y}_{x,t|j}$ as total income of an individual in state x (aged j, a state that is part of x but made explicit) at time t given as

$$\tilde{y}_{x,t|j} = y_{x,t} + R_t b_t + \tau_{ls,t}$$

Present discounted value of income is given as

$$Y_t = \tilde{y}_{x,t|j=1} + \sum_{j=2}^{J} \left(\prod_{k=2}^{j} \frac{s_k}{R_{t+k-1}} \right) \tilde{y}_{x,t+j-1|j}$$

Since

$$(1+\tau_c)(C_{1,t} + C_{2,t}) = Y_t,$$

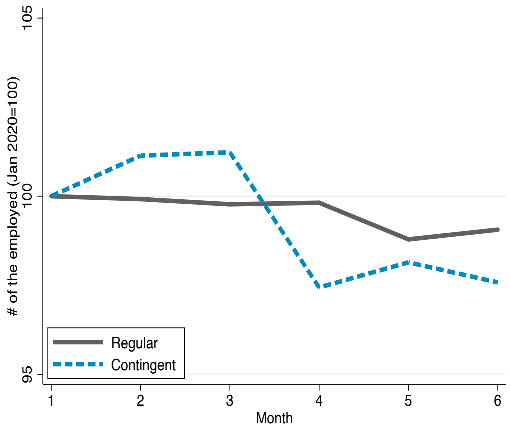
$c_{1,t}$ is computed as

$$c_{1,t} = \frac{Y_t/(1+\tau_c)}{\left[1 + \sum_{j=2}^{J} \left(\prod_{k=2}^{j} \frac{s_k}{R_{t+k-1}}\right) \left(\prod_{k=1}^{j} g^c_{1,t+k-1}\right)\right] + \frac{1-\gamma_t}{\gamma_t} \left[1 + \sum_{j=2}^{J} \left(\prod_{k=2}^{j} \frac{s_k}{R_{t+k-1}}\right) \left(\prod_{k=1}^{j} g^c_{2,t+k-1}\right)\right]}$$

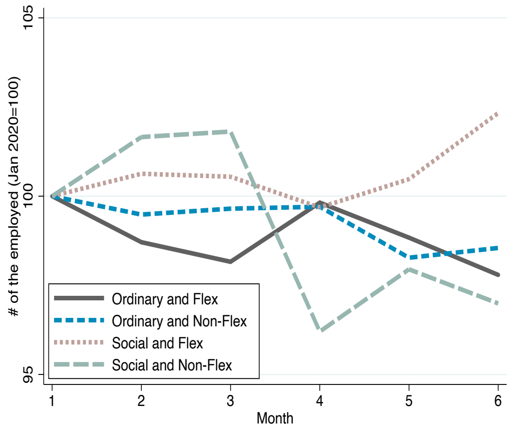
Then compute $c_{1,t}$ and $c_{2,t}$ using (6), (9) and (10). Finally, compute assets from (5) recursively.

D Seasonally Adjusted Series

This section presents seasonally adjusted versions of employment series, corresponding to the raw data series shown in Figures 2, 3, and 5 in the main text. We confirm that the main message of the paper is not overturned by seasonal adjustments.



(a) By Employment Type



(b) By Sector and Occupation

Figure D.16: Changes in Employment (Jan. 2020 = 100, Seasonally Adjusted)

Note: Figure D.16a shows the number of employed by employment type in each month between January and June 2020, based on samples of workers aged 25 to 64. Figure D.16b shows the number of employed by sector and occupation categories. The samples include workers aged 15 to 64, differently from Figure D.16a, since data by more granular categories is not available from the publicly available aggregate data. For the same reason, samples in Figure D.16b include not only regular and contingent workers but also other types of workers such as the self-employed. In both figures, the values in January 2020 are normalized to 100, and series are seasonally adjusted. The data is from Labor Force Survey (LFS) by the Ministry of Internal Affairs and Communications (MIC).

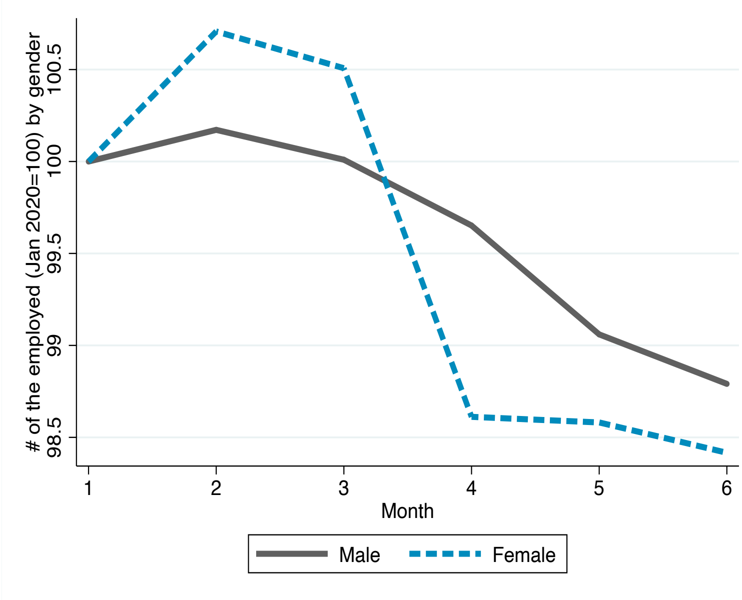
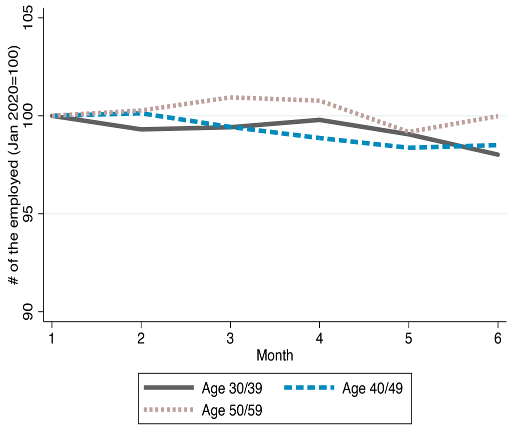
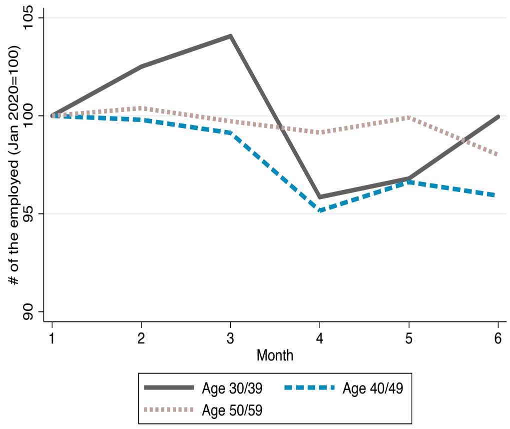


Figure D.17: Changes in Employment by Gender (Jan. 2020 = 100, Seasonally Adjusted)

Note: Figure D.17 shows the number of employed by gender in each month between January and June 2020. We restrict samples to workers aged 25 to 64. The values in January 2020 are normalized to 100, and series are seasonally adjusted. The data is from Labor Force Survey (LFS) by the Ministry of Internal Affairs and Communications (MIC).



(a) Regular Workers



(b) Contingent Workers

Figure D.18: Changes in Employment by Age Group (Jan. 2020 = 100, Seasonally Adjusted)

Note: Figure D.18a shows the number employed by age for regular worker in each month between January and June 2020. Figure D.18b shows the number of employed by age for contingent workers during the same period. The values in January 2020 are normalized to 100. Samples are restricted to workers aged 25 to 64. Series are seasonally adjusted. The data is from Labor Force Survey (LFS) by the Ministry of Internal Affairs and Communications (MIC).