Age, Industry, and Unemployment Risk During a Pandemic Lockdown

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Abstract

This paper models the macroeconomic and distributional consequences of lockdown shocks during the COVID-19 pandemic. The model features heterogeneous life-cycle households, labor search, employment risk, and multiple industries. We present an application to New Zealand, where the health effects of the pandemic were especially mild relative to other countries. This allows us to study the effects of lockdowns absent demand shocks induced by health concerns about the virus itself. We use model counterfactuals to study the impact of a large wage subsidy scheme implemented in New Zealand. We find that the subsidy prevented a large number of job losses, saving around 6.8% of steady state employment. We then study the welfare consequences of several alternative fiscal interventions during the pandemic. While the wage subsidy prevents much unemployment among young households, we find that they enjoy larger welfare gains from a policy that raises unemployment benefits during the pandemic.

Keywords: COVID-19, Pandemic, Lockdowns, Unemployment Risk, Wage Subsidy, Life-Cycle, Consumption

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1. Introduction

The COVID-19 pandemic of 2020 was the cause of enormous macroeconomic disruptions around the world. These macroeconomic shocks were the result of restrictions on producer and consumer activity (i.e. lockdowns), as well as decreased demand due the health concerns associated with contracting the virus. In response, governments around the world quickly implemented large fiscal interventions in the form of wage subsidies, loans to firms, and direct transfers to households. In addition, the effects of the pandemic were disproportionately felt by particular types of firms and workers, implying significant heterogeneity in the economic outcomes experienced by different households.

This paper studies the macroeconomic and distributional consequences of lockdowns imposed during the global pandemic. In general, pandemic recessions are the result of both supply and demand shocks, which complicates identification of the economic impact of lockdowns on their own. For this reason, we build a model of the pandemic calibrated to data from New Zealand, which presents a near natural experiment during this period. Because New Zealand is a remote island nation, and because its government quickly closed international borders and imposed a strict nation-wide lockdown, the virus was effectively eliminated in the community by early June 2020.[1] As a result, the health effects of the pandemic and their consequences for consumer demand have been limited.[2] Note that this is in stark contrast to the effects of the pandemic in countries like the USA.[3] Thus, the experience of New Zealand presents a useful case study for investigating the macroeconomic effects of lockdowns in isolation.

We study the macroeconomic and distributional effects of lockdowns in a heterogeneous agent model with labor market search frictions, multiple industries, and under a small open economy assumption. Households in the model are heterogeneous in age, wealth, employment status, and industry of employment. They choose how much to consume and save over their life-cycle, subject to fluctuations in employment determined by the labor market. After labor market search takes place, matches between workers and firms are subject to idiosyncratic match productivity shocks, which can result in endogenous job separations. Because match productivity varies with worker age, job separation rates decline over the life-cycle which helps to generate the life-cycle profile of employment risk observed in the data. Firm productivity also varies with industry, which leads to cross-industry variation in both wages and employment risk. Finally, workers stochastically transition across industries following job separations, which helps to capture the life-cycle profile of industry employment composition.

In the model, we characterize a lockdown as a sequence of negative shocks to industry-level productivity. These productivity shocks capture the impact of a lockdown since they imply

[1] For a timeline of key events in New Zealand during the pandemic, see https://covid19.govt.nz/alert-system/history-of-the-covid-19-alert-system/.

[2] For example, retail spending via debit, credit, and charge cards had largely recovered to pre-COVID levels by June 2020. See https://www.stats.govt.nz/information-releases/electronic-card-transactions-november-2020.

[3] Using a variety of micro-data sources gathered during the early phase of the pandemic, Chetty et al. (2020) showed that greater virus spread was associated with larger reductions in spending, particularly at firms in industries that required a lot of in-person interaction.

that firms cannot utilize labor resources at their previous rates. We assume that firms in the services industry are disproportionately impacted by a lockdown, since they typically rely on more customer interaction than firms in other industries. Moreover, service sector firms such as those in tourism, accommodation, and travel industries have been disproportionately affected by ongoing restrictions on international travel. These shocks then imply differential household exposure to lockdowns through the distribution of employment across industry and age. As is the case in the data, young workers are much more likely to be employed in the services sector, and so are much more exposed to the effects of a lockdown shock than are older workers. Because endogenous job separation rates are counter-cyclical, the primary effect of the lockdown shock comes through increases in unemployment, predominantly in the service sector industry.

We use the model environment to study the effects of the wage subsidy scheme introduced by the New Zealand government in the wake of the pandemic. This policy represented an exceptionally large fiscal intervention: between March and June 2020 the wage subsidy scheme paid firms approximately 50% of the median wage for each worker employed and the scheme supported approximately 75% of the New Zealand labor force.[4] In order to limit the subsidy to those firms most affected by the pandemic, the government stipulated that firms must observe a 30% decline in revenues over the previous 30 days to be eligible. In the model, we introduce a revenue-dependent subsidy policy and calibrate it to capture the 75% of firm-worker matches that received the subsidy during the first quarter of the pandemic. Because revenues fall by more for firms in the service sector and with younger workers, we show these firms are significantly more likely to receive the wage subsidy. This suggests that the conditional wage subsidy scheme was reasonably well-targeted, in that most benefited workers and firms disproportionately affected by the lockdown.

In order to discipline the model parameters, our calibration strategy targets salient features of the macroeconomy prior to and during the pandemic. We calibrate the steady state of the model to capture the cross-sectional distribution of wages, employment, and employment risk by age and industry using data on the New Zealand labor market immediately prior to the pandemic. We calibrate the sequence of lockdown shocks to match the relative declines in employment across the services and non-services sectors in the first two quarters of the pandemic. And we calibrate the policy parameters to match the size of the wage subsidy received and the fraction of employees supported by the subsidy. As in the data, the lockdown shocks generate a 5.2% decline in service sector employment and a 1% decline in non-services employment in the first quarter of the pandemic after taking into account the availability of the wage subsidy scheme.

In order to study the effects of the lockdown and wage subsidy scheme, we compare the baseline model to a counterfactual model absent the subsidy policy. In aggregate, we find that the wage subsidy policy saves a large number of jobs, equivalent to 6.8% of the steady state labor force. Because both the pandemic and wage subsidy disproportionately affect the service sector, the wage subsidy saves 8.9% of service sector jobs and 5.4% of non-service sector jobs. We show that the wage subsidy works by increasing the flow profits of employers, which prevents

[4]See Section 2 for details.

firm shutdowns thereby reducing the job separation rate. Because employment relationships are preserved, fewer workers fall into unemployment than would be the case absent the wage subsidy policy. Lower unemployment and smaller declines in expected income result in much smaller fluctuations in aggregate household consumption than would have occurred absent the subsidy.

Despite the benefits of the wage subsidy, young households experience larger increases in unemployment than older households. Thus, the effects of the lockdown are disproportionately borne by the young and service sector workers, even after the subsidy is taken into account. Young households have lower stocks of savings than older households, and so are less able to insure themselves against unemployment shocks. As a result, consumption for the youngest households falls by nearly 10% during the pandemic. In contrast, older households almost perfectly smooth consumption throughout the lockdown.

Finally, with the structural model in hand we can study counterfactual policy responses to the pandemic. As alternatives, we consider a policy that raises unemployment benefit payments, and another policy that pays lump-sum transfers to all households. In order to compare policies on a dollar-for-dollar basis, we assume that each policy alternative implies the same total fiscal transfers expenditure (i.e. unemployment benefits, wage subsidies, and lump-sum transfers). While the alternative policies do not dampen employment fluctuations during the lockdown, we find that raising unemployment benefits results in more consumption smoothing among young households than does the wage subsidy policy. Since employed youth earn lower wages to begin with, higher unemployment benefits represent a large increase in unemployment insurance for those most likely to use it.[5] A welfare analysis of the policy alternatives shows that young households are much more likely to favour the policy that raises unemployment benefits. Middle-age and older households much prefer the wage subsidy policy because although their unemployment risk is relatively low throughout the pandemic, the higher wages earned later in life implies larger costs of job loss.

1.1. Literature Review

Many early papers in the macroeconomic literature on COVID-19 incorporated epidemiological model features in order to study the evolution of health and economic outcomes during the pandemic (Berger et al., 2020; Eichenbaum et al., 2020; Krueger et al., 2020; Acemoglu et al., 2020; Kaplan et al., 2020). These papers show both that households optimally reduce consumption in response to the health risks of COVID-19, and that country-wide lockdowns imply a strong tradeoff between health outcomes and economic activity. In the current paper, we focus on the effect of lockdowns alone, thereby concentrating our analysis on an extreme point along the tradeoff schedule discussed in the literature. We focus on the example of New Zealand, where early and strict lockdowns led to virtual elimination of the virus within the community. Here, the primary concern of economists and policymakers is not tradeoff between health and the economy, but the macroeconomic and distributional consequences of the

[5] Graves (2020) shows that the presence of unemployment insurance helps to smooth the consumption response of low-wealth households to aggregate shocks that generate higher unemployment risk.

lockdowns themselves.

Studying outcomes in a country like New Zealand also helps to alleviate concerns about endogeneity between the economic effects of lockdowns and endogenous household responses to the health risks of COVID-19. We model lockdowns as sequences of sectoral supply shocks, and we then attribute all economic outcomes during the pandemic to the effect of these shocks (and the fiscal policies that accompanied them; see below). The use of supply shocks to model the effects of the pandemic follows several other papers in the literature. Guerrieri et al. (2020) show that in an incomplete markets model the combination of sectoral supply shocks and liquidity constrained households can generate Keynesian demand spillovers. In a model with firm entry and exit, Bilbiie et al. (2020) show that a pandemic generated by a negative aggregate supply shock can also lead to Keynesian demand spillovers. Note, too, that Bloom et al. (2020) provide some direct empirical support for the supply shock hypothesis, showing that total factor productivity in the UK is likely to have been significantly lower during 2020 due to firms having to respond to various COVID containment measures.

In order to capture heterogeneity in the effects of a pandemic and associated lockdowns, many papers build models with multiple sectors and differential exposure to shocks. Baqaee et al. (2020) and Farhi et al. (2020) study production-based economies in which sector-specific shocks are amplified through input-output linkages built into supply chains in the model. Farhi et al. (2020) show that pandemic shocks lead to higher unemployment that is concentrated in the most heavily affected sectors. Gregory et al. (2020) study the effect of lockdowns on the labor market in a directed search model with multiple industries. They argue that service sector workers experience greater job risk, which leads to a much slower recovery in the service sector as those workers take longer to find stable employment. Kaplan et al. (2020) model workers as having differential exposure to pandemic shocks through the type of work they are involved in. Workers in occupations or industries that cannot easily work from home experience much larger declines in income than others. In our paper, we capture these differential household exposures to the pandemic through both industry of employment and worker age. We show that younger workers are much more likely to be employed at firms in the services sector, which in turn were much more exposed to the effects of lockdowns than were other firms.

Several papers in this literature build structural macroeconomic models to assess the effects of various fiscal policy responses to the pandemic. Carroll et al. (2020) build a partial-equilibrium heterogeneous agent life-cycle model to study the effects on consumption of higher unemployment insurance payments and direct stimulus checks under the US CARES Act of 2020. They show that direct transfers help stabilize consumption expenditure in the short term, but that increases in unemployment insurance are more effective if the employment effects of the pandemic are likely to persist. Bayer et al. (2020) builds a general equilibrium HANK model to study the same policies, and show that higher unemployment benefits generate larger fiscal multipliers than transfers because they offset the effects of higher unemployment risk. Faria-e-Castro (2020) studies a DSGE model with borrowers and savers, and shows that borrowers value fiscal interventions that most resemble direct cash payments: either lump-sum transfers or higher unemployment insurance payments. In the current paper, we show that New Zealand's wage subsidy scheme was very effective in preserving employment relationships during the pandemic which in turn helps to stabilize aggregate consumption. However, as in the above-cited literature, we also find that young households, who tend to be less wealthy, benefit more from a policy that raises unemployment benefits. This is because higher unemployment benefits raise the insurance value of unemployment, whereas wage subsidies only preserve incomes conditional on remaining employed.

Finally, in order to capture a realistic age-distribution of exposures to pandemic shocks, our model incorporates several important features from the previous literature on labor market search frictions. First, we build a model with life-cycle workers and un-directed search, following Lugauer (2013), De la Croix et al. (2013), Chéron et al. (2013). In the steady state of the model, young workers are more likely to be unemployed as it takes time for workers to search and find work. Second, our model features endogenous job separations, following Den Haan et al. (2000) and Fujita et al. (2012). We extend those models to allow separation rates to differ across both industries and the life-cycle, so that young and service sector workers face higher unemployment risk through job separations as observed in the data. In our model, lockdown shocks disproportionately reduce the profitability of firms hiring young and service sector workers. This raises job separation rates and thus disproportionately increases unemployment risk for these group of workers. Finally, we follow the recent literature studying the effect of employment risk in models with household heterogeneity and frictional labor markets (see Gornemann et al., 2016; Ravn et al., 2017; Graves, 2020). As in these papers, we find that low wealth households are most affected by increases in employment risk as they are less able to insure against unemployment. Thus, young and poor households gain most from higher unemployment payments during the pandemic as they benefit from the higher insurance value of unemployment (see Graves, 2020).

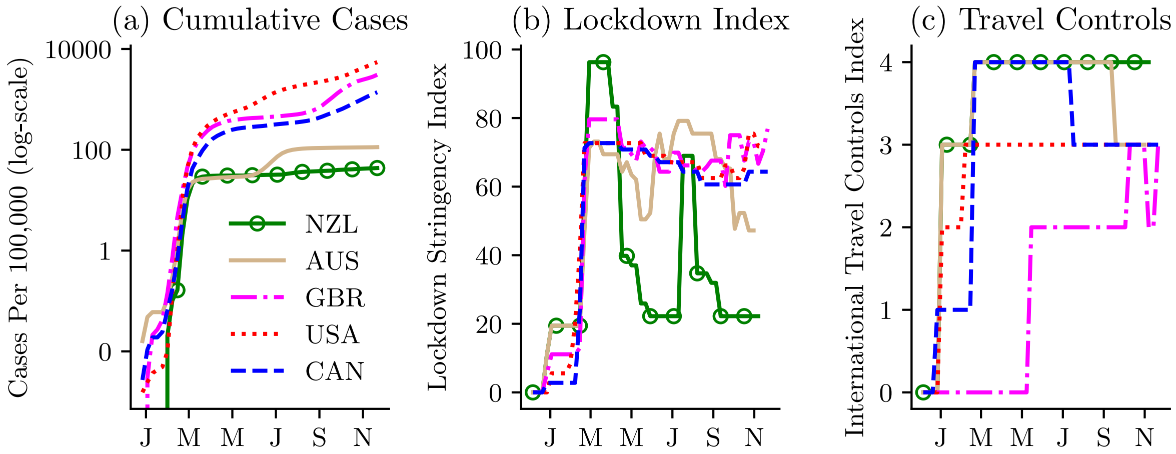
2. Motivating Evidence From New Zealand

The global outbreak of COVID-19 in 2020 was associated with significant macroeconomic disruption. However, the evolution of the pandemic in New Zealand presents an interesting case-study due to its relatively swift and stringent lockdowns, and the limited spread of the virus within its borders. The strict lockdowns imposed in New Zealand imply potentially large declines in economic output due to restrictions on productive activity, while the small COVID case-load suggests a very limited role for declining domestic demand due to health concerns. This is in stark contrast to the experience of countries such as the US, where reductions in activity due to fear of the virus seems to have dominated the effects of the lockdowns themselves (Chetty et al., 2020).

Figure 1 tracks the evolution of the virus and the imposition of lockdowns across several countries, using data collated by authors at Oxford University (Hale et al., 2020).[6] Figure 1(a) shows that New Zealand experienced an outbreak of COVID cases along with other countries at the beginning of 2020. However, case numbers in New Zealand stabilized quickly. As at

[6] COVID-related data from https://coronavirus.jhu.edu/, with population data from https://data.oecd.org/pop/population.htm.

Figure 1: COVID-related Lockdowns by Country



Notes: The overall lockdown stringency index includes information about school, workplace, and public transport closures, restrictions on social gatherings, stay-at-home requirements, and restrictons on internal and international travel.

Source: Corona Virus Government Response Tracker from Oxford University (Hale et al., 2020). Population data from the OECD

December 2020, New Zealand had just 43 cumulative cases per 100,000 people. This compared favourably to case numbers per 100,000 in countries such as Australia (112), Canada (1133), Great Britain (2600), and the US (4553). Rapid and extensive lockdowns in March 2020 are one reason cited for New Zealand's success in limiting the spread of the virus. Figure 1(b) compares the timing and stringency of restrictions on social and economic activities in response to the pandemic. The data shows that New Zealand imposed some of the strictest lockdown measures of any country in early March.[7] By May, as the number of new and active cases fell, restrictions on activity in New Zealand were gradually lifted. This contrasted with many other countries, where various restrictions remained in place throughout the year.[8]

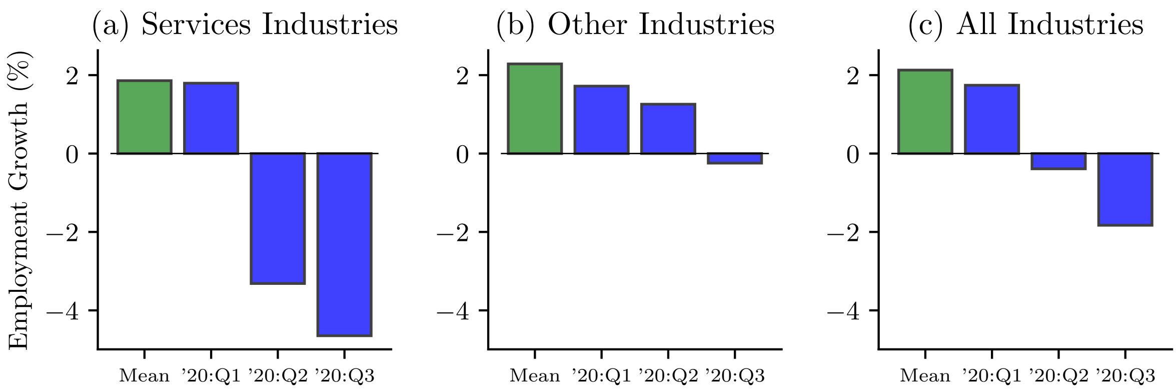
Another important factor in accounting for New Zealand's success in dealing with the pandemic is that it is an isolated island nation. This enabled New Zealand to exercise strict control over international border crossings. This is reflected in Figure 1(c) which shows that New Zealand quickly implemented international travel restrictions, which it has maintained throughout 2020. The large reduction in international travel, in conjunction with mandatory quarantine for the few travelers entering the country, has significantly reduced the number of imported COVID cases that can then be spread throughout the population.

The limited health effects of COVID-19 in New Zealand suggest that there was a relatively small role for health-related declines in demand for goods and services. However, the strong lockdowns imposed in New Zealand suggest a potentially large impact on economic activity.

[7]For details of the various rules governing lockdowns in New Zealand, see https://covid19.govt.nz/alert-system/about-the-alert-system/.

[8]In August 2020 New Zealand's largest city, Auckland, experienced a brief resurgence in COVID cases. This prompted the government to impose a short-lived lockdown in the city, as is reflected in the jump in lockdown stringency for New Zealand shown in Figure 1(a).

Figure 2: Changes in Employment by Industry During the Pandemic



Notes: Historical average of annual employment growth rates computed using data from 2009:Q1 to 2019:Q4.
Source: Authors' calculations using the Household labor Force Survey (2018)

Table 1: Employment Shares by Industry and Sector

Service Sector		Non-Service Sector	
Industry	Share	Industry	Share
Arts, Recreation and Other Services	0.060	Agriculture, Forestry and Fishing	0.049
Financial and Insurance Services	0.032	Construction	0.087
Information Media and Telecommunications	0.016	Education and Training	0.086
Rental, Hiring and Real Estate Services	0.020	Electricity, Gas, Water and Waste Services	0.009
Retail Trade and Accommodation	0.147	Health Care and Social Assistance	0.109
Transport, Postal and Warehousing	0.046	Manufacturing	0.092
Wholesale Trade	0.040	Mining	0.002
		Not Specified	0.016
		Professional, Scientific, Technical, Administrative and Support Services	0.128
		Public Administration and Safety	0.062

Notes: Employment shares computed from both paid and self-employed workers across ANZSIC06 industries for 2019. Sectoral allocation chosen by authors for the purposes of the current study.
Sources: Author's calculations using data from the Household Labour Force Survey.

Additionally, while domestic lockdowns in New Zealand were short-lived, international travel restrictions are ongoing. This suggests differential economic impacts across sectors more or less exposed to international tourism and travel.

To illustrate the economic effects of these lockdowns in New Zealand, Figure 2 shows annual employment growth across industries during the first three quarters of 2020 relative to historical averages. We split industries into service sector and non-service sector groups, where definitions and the employment composition of each are reported in Table 1.[9] We consider these broad groups of industries for two reasons. First, as noted in the recent literature, service sector workers are less likely to be able to work from home than other workers, differentially affecting economic activity during the lockdown (see Dingel et al., 2020; Bartik et al., 2020). Second, many industries in services are heavily dependent on international travelers. For example, in New Zealand in 2019 purchases by international tourists comprised 95% of accommodation services, 42% of food and beverage services, and 25% of arts and recreation services (Zealand, 2020). These industries are especially adversely affected by ongoing international border closures.

Figure 2(a) shows that service sector employment fell by 3% in the second quarter, and by over 4% in the third quarter. In contrast, Figure 2(b) shows that non-services employment growth was positive at 1% in the second quarter, and fell by just -0.1% in the third quarter.[10] Insofar as employment growth reflects the growth of economic activity, the data suggests that service sector industries experienced a far larger contraction during the pandemic than did non-service industries. We take this as evidence of significant heterogeneity in the effects of lockdowns across industries.

In anticipation of the economic effects of the pandemic, the New Zealand government implemented a broad-based wage subsidy scheme.[11] This subsidy was similar to policies adopted in other countries at this time.[12] In New Zealand, firms and self-employed workers could apply for a wage subsidy from 1 March 2020 that paid a flat rate of NZ$585.80 per full-time employee per week and was available for eight weeks.[13] The subsidy was equivalent to approximately 50% of median weekly earnings for full-time workers in 2020.[14] Receipt of the wage subsidy was subject to several conditions: firms expected a 30% drop in revenue over the previous month due to the pandemic; firms must retain subsidized employees for the duration of the subsidy; and firms must continue to pay employees at least 80% of their usual wages for the duration of the subsidy.

Figure 3 shows that around 70% of all employees in New Zealand were supported by the subsidy between March and June 2020. Limited extensions of the wage subsidy were available between June and September, but many fewer firms received these payments. Due to broad coverage and high take-up, the subsidy was an expensive fiscal intervention with NZ$14 billion paid out in 2020, equivalent to 40% of total government expenditure on social security in

[9]Our definition of service sector industries excludes the following industries: education and training; health care and social assistance; professional, scientific, and technical services; public administration and safety. We make these exclusions because the heavy involvement of the government in these industries in New Zealand limits their exposure to the market-based effects of pandemic.

[10]Note that New Zealand's first COVID case was not reported until February 28, and the government's response to the pandemic began in March (Hale et al., 2020). The first economic effects of the pandemic are largely not visible in quarterly data until 2020:Q2.

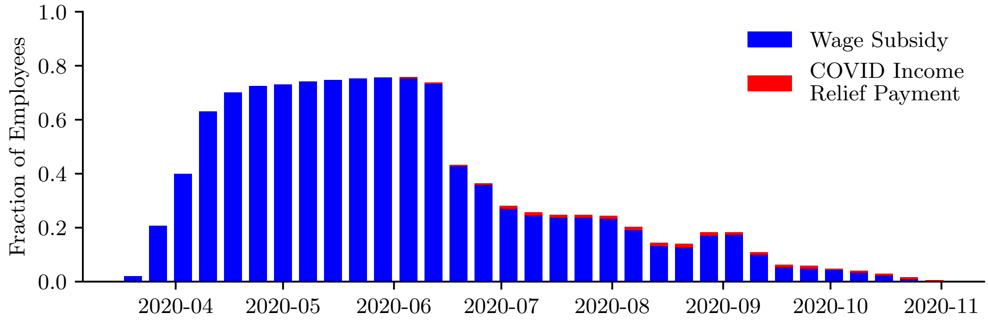
[11]For details, see https://www.workandincome.govt.nz/covid-19/wage-subsidy/index.html.

[12]For example, see Bishop et al. (2020) for an empirical analysis of the Job Keeper scheme adopted in Australia.

[13]Employers of part-time workers were eligible for NZ$350 per worker per week.

[14]Household income statistics from the Household labor Force Survey are available from Statistics New Zealand at http://nzdotstat.stats.govt.nz/.

Figure 3: New Zealand Wage Subsidy and Income Relief Payment Schemes



Notes: Number of wage subsidy and COVID income relief recipients divided by total number of employees. Number of employees measured using Monthly Employment Indicators data.
Source: Statistics New Zealand and Ministry of Social Development.

2019.[15] The New Zealand government also provided other fiscal interventions in response to the pandemic, but these were much smaller in scope. For example, unemployment benefit rates were effectively doubled for workers that lost jobs as a result of the pandemic between March and November 2020.[16] However, as Figure 3 shows, the number of workers supported by these additional unemployment payments was dwarfed by the number of workers receiving the wage subsidy.

Finally, we consider the likely distributional impacts of the pandemic by worker age. Figure 4 illustrates industry composition, job separation rates, and earnings by industry and age using data from the Linked Employer-Employee Database (LEED) for 2018.[17] The data reveal distinct life-cycle patterns in employment composition, employment risk, and earnings. Figure 4(a) shows that young workers are significantly more likely to find themselves employed in the service sector than are older workers. Figure 4(b) shows that both young and service sector workers face higher rates of job separation than older and non-service sector workers, and are thus far more likely to leave their current place of employment in any given period.[18] Figure 4(c) shows that young workers earn less than older workers in both sectors, while service sector workers earn less than non-service sector workers at all ages.

Taken together, these facts suggest that younger workers are likely to be disproportionately affected by the effects of the pandemic. Because the pandemic disproportionately affected the service sector, as illustrated in Figure 2, younger workers are more likely to lose their jobs.

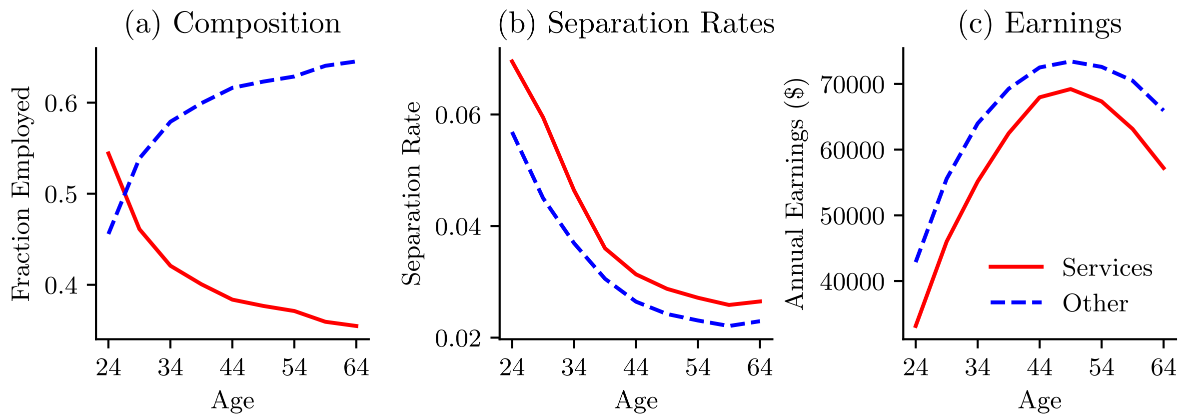
[15] The cost of wage subsidy scheme is reported by the Ministry of Social Development at https://www.msd.govt.nz/about-msd-and-our-work/publications-resources/statistics/covid-19/index.html. Data on fiscal expenditure is reported by the New Zealand Treasury at https://www.treasury.govt.nz/information-and-services/financial-management-and-advice/revenue-and-expenditure.

[16] Information on the COVID income relief payment is reported by the Ministry of Social development at https://www.workandincome.govt.nz/covid-19/income-relief-payment/index.html.

[17] Statistics New Zealand maintains LEED, which is compiled from administrative data associated with New Zealand's tax system. This covers all workers at businesses and organizations producing goods and services in New Zealand with revenue greater than $30,000.

[18] Note that job separations data encompass both employee layoffs and quits, which means that separations may result in either unemployment or a job-to-job transition.

Figure 4: Employment and Job Separation Rates by Industry Group and Age



Source: Authors' calculations using Statistics New Zealand's Linked Employer-Employee Data.

Moreover, these are workers that already face higher employment risk and are compensated with lower earnings. Young workers are thus more likely to be affected by the pandemic, but also the least able to weather its effects. For this reason, it is important to understand the distributional consequences of the fiscal interventions undertaken during the COVID-19 pandemic.

3. Model

We build a structural macroeconomic model in order to study the aggregate and distributional consequences of a pandemic-induced lockdown in New Zealand. The main model ingredients are life-cycle heterogeneous agents, multiple industries, frictional labor markets, endogenous employment risk, and exogenous productivity shocks. Our model features are motivated by three main considerations. First, the strict lockdowns and limited health effects experienced by New Zealand suggest a much stronger role for supply shocks than for demand shocks. For this reason, we model a lockdown as a sequence of productivity shocks reducing the ability of firms to produce using a given level of labor inputs. Second, there is significant heterogeneity in the effect of lockdowns on production across industries. For this reason, we model firms as being more or less exposed to the negative productivity shocks accompanying lockdowns. Third, the effects of a lockdown are likely to differ by age. Our model replicates the life-cycle profile of employment across industries, which captures the fact that young workers are disproportionately exposed to a lockdown through higher rates of employment in the services sector. Additionally, the model mimics the age distribution of employment risk so that young workers are more likely to be laid off following a shock than are old workers. We believe these features provide a plausible basis for analyzing the consequences of pandemic shocks and the fiscal responses to them.

3.1. Households

Households live for a finite number of periods, where their age is indexed by $k \in [1, \cdots, K]$. At age $K+1$ households retire and consume their remaining networth. The problem of a household of age k is:

$$\begin{aligned} V_k(b, e, i) &= \max_{c, b' \geq 0} \; u(c) + \beta \mathbb{E}\left[V_{k+1}(b', e', i')\right] \\ \text{s.t.} \quad & c + b' = (1-\tau_y)\left[e w_{i,k} + (1-e)\omega_u\right] + b(1 + (1-\tau_y)r) \\ & e', i' \sim \Gamma_{k,e,i} \end{aligned} \tag{1}$$

Above, e denotes the employment status of the household, where $e \in \{0, 1\}$ reflects unemployment and employment, respectively. The industry of employment is indexed by $i \in \{1, 2\}$, where $i = 1$ indicates the services sector, and $i = 2$ is all other industries. The household chooses consumption c, and liquid asset holdings b, where the latter is subject to a no-borrowing constraint. In retirement, households consume all remaining networth b, where final period utility is weighted by ψ_w:

$$\begin{aligned} V_{K+1}(b) &= \psi_w u(c) \\ c &= b \end{aligned} \tag{2}$$

Household income depends on age, employment status, and industry of employment. If employed, the household receives a wage $w_{k,i}$, which differs by age and industry. Unemployed households receive a constant unemployment benefit ω_u. All household income, including interest income on assets, is taxed at rate τ_y. Income is subject to idiosyncratic risk due to changes in employment status and industry of employment. This risk is characterized by a Markov chain $\Gamma_{k,e,i}$, which is exogenous from the perspective of the household. However, the parameters of the Markov chain are governed by the outcomes of a labor market search processes, described in more detail in Sections 3.3.

The final consumption good c is a composite of services and other goods consumption via an Armington aggregator:

$$c = \left[\chi^{\frac{1}{\varepsilon_c}} c_1^{\frac{\varepsilon_c - 1}{\varepsilon_c}} + (1-\chi)^{\frac{1}{\varepsilon_c}} c_2^{\frac{\varepsilon_c - 1}{\varepsilon_c}}\right]^{\frac{\varepsilon_c}{\varepsilon_c - 1}} \tag{3}$$

Above, ε_c gives the elasticity of substitution between the two types of consumption. The solution to the expenditure minimization problem implies the following consumption demand functions

$$c_1 = \chi \left(\frac{p_1}{p}\right)^{-\varepsilon_c} c, \quad c_2 = (1-\chi)\left(\frac{p_2}{p}\right)^{-\varepsilon_c} c, \tag{4}$$

where $\frac{p_i}{p}$ is the relative price of consumption in industry i, and the aggregate price index is given by

$$p = \left[\chi p_1^{1-\varepsilon_c} + (1-\chi) p_2^{1-\varepsilon_c}\right]^{\frac{1}{1-\varepsilon_c}}. \tag{5}$$

3.2. Production Firms

Competitive firms in each industry produce output Y_i via linear production technologies $Y_i = Z_i\tilde{N}_i$, where Z_i is industry-specific productivity, and $\tilde{N}_i$ is efficiency-adjusted units of labor. Firms maximize real profits

$$\max_{\tilde{N}_i} \frac{p_i}{p} Y_i - h_i\tilde{N}_i$$

where $\frac{p_i}{p}$ is the relative price of output, and h_i is the industry-specific real wage rate per efficiency unit of labor.

3.3. labor Markets

labor markets in each industry feature search frictions. Unemployed households search for work in their current industry i, while labor market entrepreneurs in each industry post vacancies to attract workers in that industry. Let v_i be the number of vacancies posted by entrepreneurs in industry i, and u_i is the total mass of workers searching for work in industry i. The matching technology is a Cobb-Douglas function given by

$$m(u_i, v_i) = M_i u_i^{\alpha} v_i^{1-\alpha},$$

where M_i is industry-specific match productivity, and α is the matching elasticity. The rate at which entrepreneurs fill vacancies is defined as $q_i^v = \frac{m(u_i,v_i)}{v_i}$. The rate at which unemployed households find jobs is defined as $q_i^u = \frac{m(u_i,v_i)}{u_i}$.

We assume that labor market entrepreneurs cannot age-discriminate between potential workers when posting job vacancies.[19] This means that entrepreneurs may be matched with workers of any age. Because households retire at age $K+1$, any existing employment relationships with age-K workers are destroyed with certainty in the following period. Entrepreneurs matched to a worker receive the industry-specific production wage h_i. But each match is subject to an idiosyncratic productivity shock x, which yields total revenue of $h_i x$ for the entrepreneur. In turn, the entrepreneur pays workers an industry- and age-specific wage $w_{i,k}$. Finally, a current match survives until the next period with probability $(1-\rho_{i,k+1})$.

The value of a filled job for an entrepreneur in industry i, matched to a worker age k, and with match-specific productivity x is

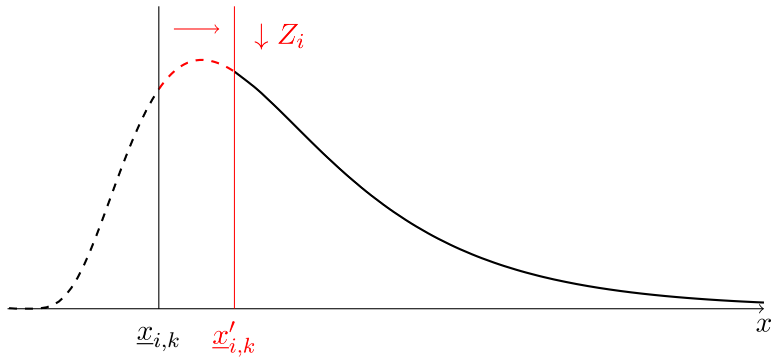
$$J_{i,k}(x) = h_i x - w_{i,k} + \beta\mathbb{E}\left[(1-\rho_{i,k+1})J_{i,k+1}(x')\right] \tag{6}$$

The match-specific productivity shock follows a log-normal distribution $\log x \sim \mathcal{N}(\mu_x, \sigma_{x,k})$, where the standard deviation $\sigma_{x,k}$ depends on age. We assume that entrepreneurs are risk-neutral, own their own firms, and that all profits earned each period are immediately consumed.

As in Fujita et al. (2012) we allow for endogenous job separations. Separations follow from endogenous firm shut-down decisions. Note that a shut down need not occur when current flow profits are negative, as entrepreneurs also consider the present discounted value of future profits.

[19] This assumption follows Lugauer (2013), who builds a model with undirected search and life-cycle workers to study the effects of demographic change.

Figure 5: Endogenous Job Separations and the Distribution of Match Productivity



Rather, an entrepreneur ceases to operate and a job separation occurs when $J_{i,k}(x) \leq 0$. This shut down condition defines a threshold productivity level

$$\underline{x}_{i,k} = \frac{w_{i,k} - \beta \mathbb{E}\left[(1-\rho_{i,k+1})J_{i,k+1}(x')\right]}{h_i}, \tag{7}$$

which depends on industry-level productivity through the production wage h_i. All job matches with idiosyncratic productivity below this threshold are destroyed. Note that separations apply to both existing employment arrangements as well as newly matched employers and employees. This means that a worker may match with and separate from an entrepreneur in the same period before production even takes place.

Figure 5 illustrates the log-normal distribution of match-specific productivity. The black vertical line indicates the threshold productivity $\underline{x}_{i,k}$ such that all matches with lower productivity are destroyed. When industry-level productivity Z_i falls, the production wage h_i also falls, which increases the threshold to $\underline{x}'_{i,k}$ as indicated by the red vertical line. The fall in aggregate productivity results in an increase in the fraction of matches that are unprofitable and which result in separations. Thus, a fall in aggregate productivity results in a larger number of job losses through employment separations.

Thus, we can derive an expression for the job separation rate using the distribution of match-specific productivity:

$$\rho_{i,k} = \int^{\underline{x}_{i,k}} \phi_k(x)dx = \Phi_k(\underline{x}_{i,k}), \tag{8}$$

where $\phi_k(\cdot)$ and $\Phi_k(\cdot)$ denote log-normal PDFs and CDFs with age-dependent standard deviations $\sigma_{x,k}$. As discussed with reference to Figure 5 above, the job separation rates $\rho_{i,k}$ are a function of aggregate productivities Z_i through the production wage h_i in the denominator of Equation (7).

labor market entrepreneurs post vacancies up to the point at which marginal benefit equals marginal cost. The real vacancy posting cost in each industry is κ_i. The marginal benefit of a vacancy is the expected value of filling a job. The job filling value function for a worker of age k is described in Equation 6. However, the expected value is governed by the probability of finding a worker q_i^v, the probability that a given worker is age k, and the probability that the employment match does not separate before production takes place. The probability that a searching worker chosen at random is aged k is $\frac{u_{i,k}}{u_i}$, where $u_i = \sum_{k=1}^{K} u_{i,k}$. The assumption of free-entry thus implies that

$$\kappa_i = q_i^v \sum_{k=1}^{K} \frac{u_{i,k}}{u_i} \mathbb{E}\left[(1-\rho_{i,k+1}) J_{i,k}(x)\right], \tag{9}$$

where the expectation is taken over idiosyncratic match productivity x, accounting for the probability that a separation occurs before production takes place.

3.3.1. Wage Determination

Because Nash bargaining is complicated by the two-sided heterogeneity of workers and firms, we follow several recent papers in the heterogeneous agents literature by assuming a simple wage setting rule.[20] In steady state, we assume that wages are determined by the marginal labor market entrepreneur. That is, wages are set by the firm that is indifferent between continuing and shutting down. For such a firm the value of a filled job is nil, and so Equations (6) and (8) yield

$$w_{i,k} = h_i \Phi_k^{-1}(\rho_{i,k}) + \beta \mathbb{E}\left[(1-\rho_{i,k+1}) J_{i,k+1}(x')\right], \tag{10}$$

where Φ_k is the CDF over match-specific productivity x.

Outside of steady state, we assume that worker wages are sticky and respond to production wages with a constant elasticity ε_w:

$$w_{i,k,t} = w_{i,k} \left(\frac{h_{i,t}}{h_i}\right)^{\varepsilon_w}.$$

3.3.2. labor Market Flows and Aggregate labor Supply

Let the number of age-k households and employees in industry i be denoted by $I_{i,k}$ and $N_{i,k}$, respectively. The number of job searchers in industry i of age-k evolves according to the following law of motion:

$$u_{i,k} = \pi_{ii}\left(I_{i,k-1} - (1-\rho_{i,k})N_{i,k-1}\right) + (1-\pi_{i'i'})\left(I_{i',k-1} - (1-\rho_{i',k})N_{i',k-1}\right) \tag{11}$$

Above, the first additive term corresponds to households in industry i last period whose jobs were destroyed but who stayed in industry i, as well as households who were unemployed in industry i, stayed in the same industry, but could not find a job. The second additive term has a similar interpretation, but tracks households in the other industry i' who were separated or were searching but but switched industries from i' to i.

The number of age-k workers employed in industry i is given by the sum of age-$k-1$ workers who kept their job this period, and the number of job searchers who found a job and survived endogenous separations:

$$N_{i,k} = (1-\rho_{i,k})N_{i,k-1} + u_{i,k} q_i^u (1-\rho_{i,k}) \tag{12}$$

[20] See, for example, Gornemann et al. (2016) and Graves (2020).

Finally, aggregate labor supply in each industry is given by total efficiency units of labor provided by working households. This consists of the total number of workers in each age group scaled by average match productivity in that age group:

$$\tilde{N}_i = \sum_{k=1}^{K} N_{i,k}\bar{x}_{i,k}$$

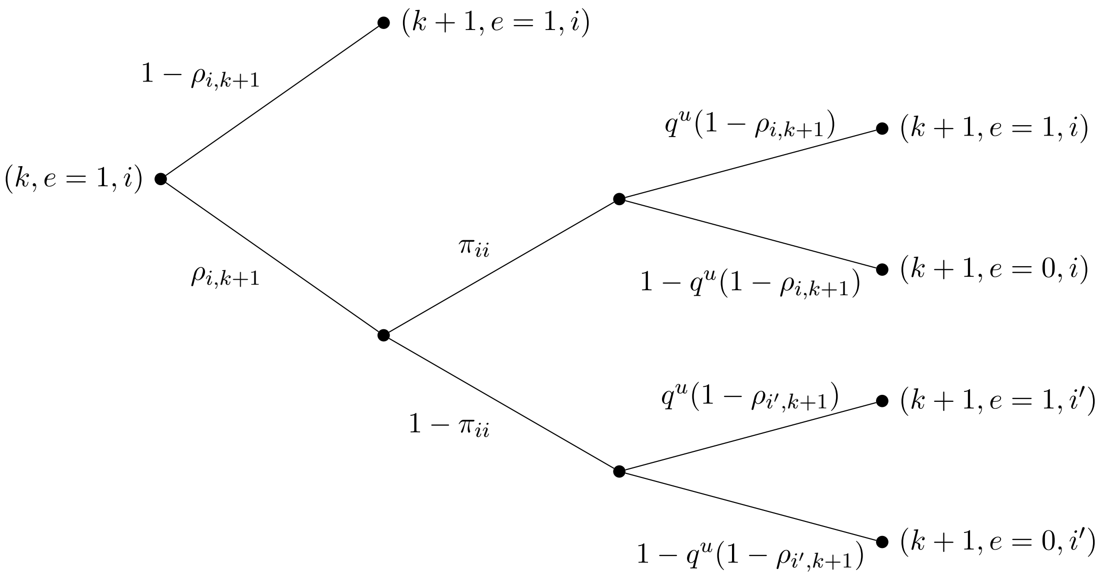
where $\bar{x}_{i,k} = \int^{\underline{x}_{i,k}} x\phi_k(x)dx$.

3.3.3. Employment and Industry Transitions

Given the labor market search environment, we are now in a position to characterize the household employment and industry transitions described by the Markov chain $\Gamma_{k,e,i}$. Households enter a period with employment status e and industry of employment i. At the end of the period, employees are subject to job separations at rate $\rho_{i,k+1}$ (i.e. separations occur prior to age $k+1$). Separated workers that were employed in industry i may then switch industries with probability $1-\pi_{ii}$. After industry transitions take place, workers search for jobs in their new industry and match with a potential employer with probability q_i^u. However, because all employment relationships are subject to match productivity shocks at the beginning of the period, even new matches may separate before production takes place. Thus, the effective job finding rate for an unemployed household is $q_i^u(1-\rho_{i,k+1})$: the probability of finding a job in addition to surviving the initial productivity shock.

Figure 6 shows an event tree illustrating the employment and industry transitions faced by age-k worker that is currently employed in industry i. The initial state vector of the worker is $(k, e=1, i)$, and the transition to outcome i' indicates that a worker has switched from industry i to another industry i'.

Figure 6: Employment and Industry Transitions Event Tree



The Markov chain $\Gamma_{k,e,i}$ can be separated into two sub-Markov chains: $\Gamma^{i,i}_{e,k}$ describes employment transitions for workers that remain in the same industry i; and $\Gamma^{i,i'}_{e,k}$ describes employment transitions for households that switch from industry i to i'. Let $[1-e, e]'$ be the state vector describing employment status. Then for each matrix the upper row reports unemployment transition probabilities, and the bottom row reports employment transition probabilities. For households remaining in the same industry i, the transition matrix is given by

$$\Gamma_{e,k}^{i,i} = \begin{bmatrix} \pi_{ii}(1-q_i^u(1-\rho_{i,k+1})) & \pi_{ii}q_i^u(1-\rho_{i,k+1}) \\ \rho_{i,k+1}\pi_{ii}(1-q_i^u(1-\rho_{i,k+1})) & 1-\rho_{i,k+1}+\rho_{i,k+1}\pi_{ii}q_i^u(1-\rho_{i,k+1}) \end{bmatrix},$$

For households that switch from industry i to i', the transition matrix is given by

$$\Gamma_{e,k}^{i,i'} = \begin{bmatrix} (1-\pi_{ii})(1-q_{i'}^u(1-\rho_{i',k+1})) & (1-\pi_{ii})q_{i'}^u(1-\rho_{i',k+1}) \\ \rho_{i,k+1}(1-\pi_{ii})(1-q_{i'}^u(1-\rho_{i',k+1})) & \rho_{i,k+1}(1-\pi_{ii})q_{i'}^u(1-\rho_{i',k+1}) \end{bmatrix}$$

Finally, the full Markov transition matrix for employment and industry transitions is

$$\Gamma_{k,e,i} = \begin{bmatrix} \Gamma_{e,k}^{1,1} & \Gamma_{e,k}^{1,2} \\ \Gamma_{e,k}^{2,1} & \Gamma_{e,k}^{2,2} \end{bmatrix} \tag{13}$$

3.4. Government

Government consists of a fiscal authority that collects taxes T_t, distributes unemployment benefits UB_t, and issues debt B_t^g at interest rate r, and conducts non-valued government expenditure G_t. The government budget constraint is

$$G_t + (1+r)B_t^g + UB_t = B_{t+1}^g + T_t, \tag{14}$$

where total unemployment benefits and tax revenues are given by

$$UB_t = \sum_{k=1}^{K}\left(\int(1-e)\omega_u d\lambda_{k,t}\right)$$

$$T_t = \tau_y\left(\sum_{k=1}^{K}\int(1-e)\omega_u d\lambda_{k,t} + \sum_{k=1}^{K}\int e w_{i,k} d\lambda_{k,t} + \sum_{k=1}^{K+1}\int rb d\lambda_{k,t} + \Pi_t\right)$$

where $\lambda_{k,t}$ is the distribution over households of age k at time t, and Π_t are labor market entrepreneur profits.

In all of the experiments reported in Section 5 we assume that government debt is held constant $B_t^g = B^g$ for all t, while government spending G_t adjusts to satisfy the budget constraint following a shock.

3.5. Equilibrium

A stationary equilibrium in the model includes: optimal household decisions that are functions of the state variables $s = (k, b, e, i)$; optimal firm and entrepreneur decisions; interest rate r; prices $\{\frac{p_i}{p}\}_{i=1,2}$; wages $\{h_i\}_{i=1,2}$ and $\{w_{i,k}\}_{i=1,2,k=1,\cdots,K}$; laws of motion for labor market searchers from Equation (11); and distributions of households over the state space that are constant over time $\{\lambda_k(s)\}_{k=1,\cdots,K}$. Given prices and optimal decisions: labor demand is equal to labor supply; goods markets clear in each industry i; the market for bonds clears; and the

Table 2: Externally Calibrated Model Parameters

Description	Parameter	Value	Source
Risk Aversion	γ	2.000	Standard
Real Interest Rate	r	0.023	Reserve Bank of New Zealand
Unemployment Benefit Rate	ω_u	0.252	Work and Income New Zealand
Services Consumption Share	χ	0.519	Statistics New Zealand
Elasticity of Substitution	ε_c	2.000	Hobijn et al. (2019)
Matching Function Elasticity	ε_m	0.750	Razzak (2009)
Real Wage Elasticity	ε_w	0.100	Authors' Estimates using LEED
Vacancy Filling Rate	q^v	0.700	Christoffel et al. (2009)

government budget constraint holds. A formal definition of the recursive stationary equilibrium is provided in the Appendix.

In the experiments conducted in Section 5, we solve for equilibrium following a series of ex-ante unexpected shocks. Along the transition path, we maintain the assumption of a small open economy. That is, the interest rate r is held constant, and the domestic economy must borrow from or save with the rest of the world. This is reflected in fluctuations in net exports in the aggregate real resource constraint:

$$\frac{p_{1,t}}{p_t}Y_{1,t} + \frac{p_{2,t}}{p_t}Y_{1,t} = C_t + \Pi_t + G_t + \kappa_1 v_{1,t} + \kappa_2 v_{2,t} + NX_t,$$

where the left side of the equation is total output, C_t is aggregate household consumption, Π_t is firm profits which are consumed by entrepreneurs during the period in which they are earned, $\kappa_i v_{i,t}$ are total vacancy posting costs for industry i, and NX_t are net exports.

4. Model Calibration

We calibrate the model so that the steady state matches a range of household and labor market characteristics in New Zealand prior to the onset of the pandemic in 2020. Importantly, the calibrated model reproduces the observed industry and age distributions of employment, employment risk, and wages. This ensures that the model captures ex-ante household exposures to pandemic shocks.

The model is calibrated at a quarterly frequency. Households are born at age 20 and work for 180 periods until retirement at age 65. Table 2 reports the other externally calibrated parameters. The risk aversion parameter γ is set to 2. The annual real interest rate is 2.3 percent, the average for the years 2000 to 2019. The unemployment benefit rate ω_w is set at 20% of the median wage, consistent with the Jobseeker Support benefit rate in 2019 for adults aged over 25. The consumption share of services χ is set to 0.519, which is the average for the years 2000 to 2019. The elasticity of substitution between services and non-services ε_c is set to

2, consistent with recent empirical evidence on substitutability between goods and services in Hobijn et al. (2019).

The matching function elasticity ε_m is set to 0.75, following empirical estimates from New Zealand in Razzak (2009). We estimate the wage elasticity ε_w using quarterly, industry-by-region LEED data from 1999-2019. We regress the log-difference in wages on the log-difference in employment, controlling for industry, region, and year fixed effects. We run OLS and instrumental variables (IV) regressions, constructing a Bartik instrument from industry shares within each region and national employment growth rates in each industry. The OLS and IV results yield elasticities of 0.078 and 0.067, respectively. Following these results we conservatively set the elasticity ε_w to 0.10. The vacancy filling rate q^v is assumed to be the same across industries, and is set to 0.70 (see Christoffel et al., 2009).

Table 3 reports internally calibrated parameters, and the moments governed by those parameters in both the model and data. Panel A reports parameters governing wealth accumulation, cross-industry earnings, and taxes. The discount factor β is set to match the ratio of networth to quarterly GDP. The utility weight on retirement ψ is set to match networth held by households in the decade prior to retirement relative to the networth held by households aged 25 to 34. Productivity in the non-services sector Z_2 is normalized to one, and the relative size of productivity in the services sector Z_1/Z_2 is set to match the ratio of average labor earnings across industries. We set the tax rate τ_y to match the ratio of government spending and GDP, since government spending is determined residually from the government budget constraint.

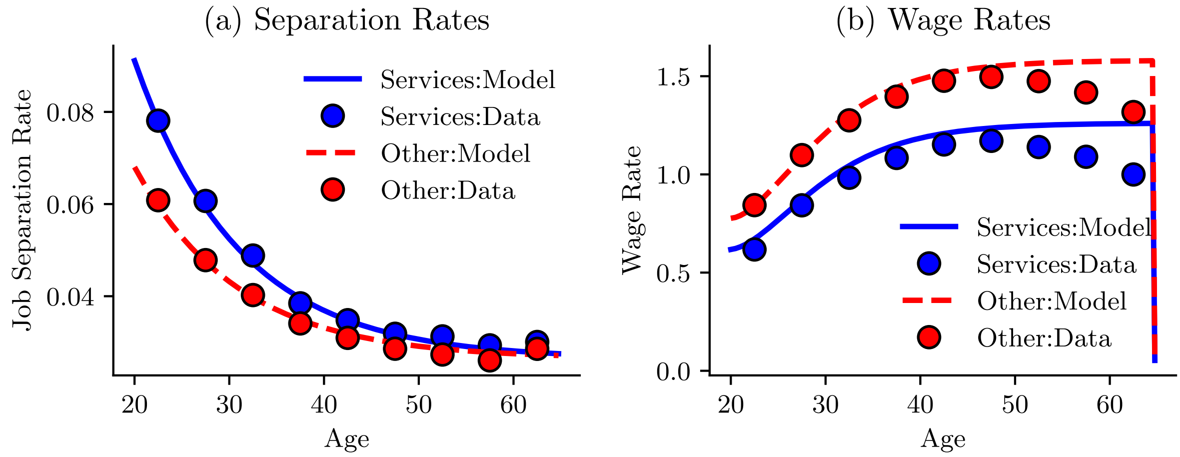
Panel B of Table 3 reports parameters that determine job separations. New Zealand's LEED data provides job separation rates by industry and by household age in 5-year age groups. Because we solve the model at a quarterly frequency, we generate job separation rates for every age using a simple auto-regressive process, $\rho_{i,k} = (1 - \rho_\rho)\mu_\rho + \rho_\rho \rho_{i,k-1}$, where μ_ρ is the average separation rate, ρ_ρ is the persistence of the process, and there is a different initial condition for each industry $\rho_{i,k=0}$. We set the parameters of the auto-regressive process so that the average separation rates by industry and age group in the model match those observed in the LEED data. Figure 7(a) shows that separation rates in the model provide an extremely close fit to the data.

Table 3: Model Parameters and Moments

Parameter		Value	Moment	Model	Data	Source
A. Miscellaneous Parameters						
Discount factor	β	0.994	Networth/GDP	0.767	0.769	RBNZ, 2019
Retirement weight	ψ	140.000	Networth: 55-64/25-34	12.068	12.099	HES, 2017
Relative productivity	Z_1/Z_2	0.385	Earnings: Non-Services/Services	1.301	1.301	LEED, 2019
Tax rate	τ_y	0.212	Government Spending/GDP	0.188	0.188	RBNZ, 2017
B. Job Separation Process Parameters						
Mean	μ_ρ	0.026	Separation rates by age	See Figure 7(a)		LEED, 2019
Persistence	ρ_ρ	0.978	Separation rates by age	See Figure 7(a)		LEED, 2019
Initial value, services	$\rho_{1,k=0}$	0.091	Separation rates by age	See Figure 7(a)		LEED, 2019
Initial value, other	$\rho_{2,k=0}$	0.068	Separation rates by age	See Figure 7(a)		LEED, 2019
C. Idiosyncratic Match Productivity Process Parameters						
Mean	μ_σ	1.250	Earnings: 30-34/20-24	1.577	1.580	LEED, 2019
Persistence	ρ_σ	0.963	Earnings: 40-44/30-34	1.171	1.170	LEED, 2019
Initial standard deviation	$\sigma_{k=0}$	0.100	Vacancy costs/GDP	0.032	0.020	Standard
D. Industry Labour Market Parameters						
Industry transition, services	π_{11}	0.879	Industry-age composition	See Figure 8(a)		LEED, 2019
Industry transition, other	π_{22}	0.936	Industry-age composition	See Figure 8(a)		LEED, 2019
Employment probability, $k=0$	$\lambda_{e=1,k=0}$	0.999	Industry-age composition	See Figure 8(a)		LEED, 2019
Services probability, $k=0$	$\lambda_{i=1,k=0}$	0.584	Jobseeker support by age	See Figure 8(b)		MSD, 2019
Job finding rate	q^u	0.601	Jobseeker support by age	See Figure 8(b)		MSD, 2019

Source: Authors' calculations using data from the Household Economic Survey, the Ministry of Social Development, the Linked Employer-Employee Database, and the Reserve Bank of New Zealand.

Figure 7: Job Separation and Wage Rates by Industry and Age

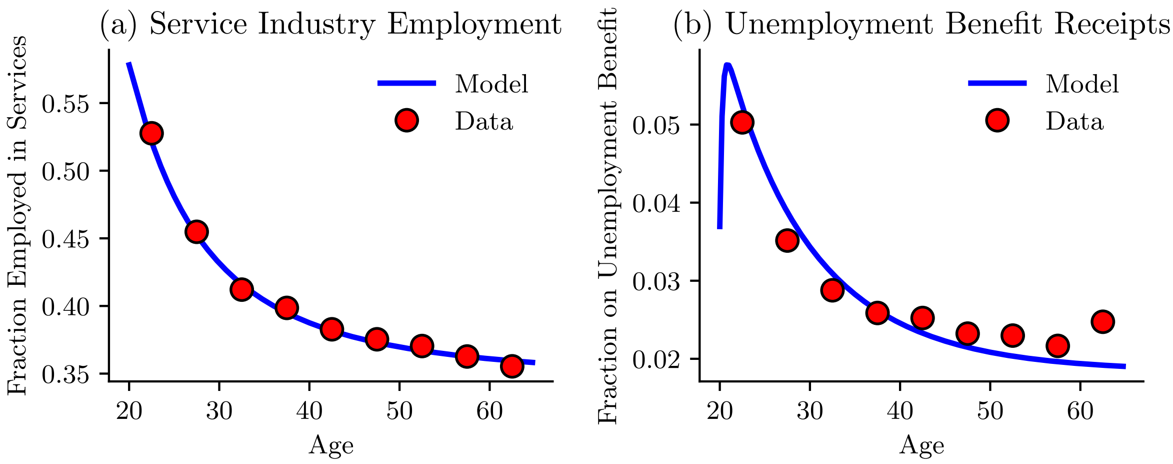


Notes: Authors' calculations and data from LEED, HLFS

Panel C of Table 3 reports the parameters of the idiosyncratic match productivity process. Recall that match productivity is distributed according to a log-normal distribution with a constant mean μ_x and age-dependent standard deviations $\sigma_{x,k}$. We normalize μ_x so that $\mathbb{E}(x|k = 1) = 1$. For parsimony, we model the age-dependent standard deviation as an auto-regressive process with mean μ_σ, persistence ρ_σ, and initial condition $\sigma_{k=0}$. Conditional on job separation rates, the match productivity process governs steady state wages $w_{i,k}$ via Equation (10). Match productivity is also related to vacancy costs through the vacancy posting Equation (9). Thus, we set the match productivity parameters to target the slope of life-cycle earnings and the vacancy costs-to-GDP ratio. Specifically, we target the earnings ratio for 30-to-34 year-old workers to 20-24 year old workers, and the ratio for 40-to-44 year-old workers to 30-to-34 year-old workers. Figure 7(b) shows the life-cycle profile of earnings for each industry in the model and the data. The model does a good job of matching the early life-cycle earnings profile. The model fails to capture the hump-shape in life-cycle earnings because the simple auto-regressive process generates a monotonically increasing variance of match productivity over age. The rising variance of match productivity is associated with a monotonically increasing wage profile, rather than the declining wage profile prior to retirement observed in the data. It is possible to generate the hump-shape wage profile, but at the cost of a more complicated parameterization of the match productivity process. Finally, note that sudden drop in wages for the oldest workers is because the continuation value of a filled job for workers immediately prior to retirement is zero, which results in the wage decline via Equation (10).

Panel D of Table 3 reports parameters for industry employment transitions and the job finding rate. These parameters include the industry transition rates $1-\pi_{11}, 1-\pi_{22}$, initial probability of employment $\lambda_{e=1,k=0}$, initial probability of working in the services sector $\lambda_{i=1,k=0}$, and the job finding rate q^u. Note that we allow industry transition rates to differ across industries, but assume that the job finding rate q^u is the same across industries in the steady state. We use a simulated method of moments procedure to choose these parameters by matching the

Figure 8: Industry Composition and Unemployment Benefit Receipts by Age



Notes: Authors' calculations and data from HLFS, MSD

life-cycle profiles of industry employment composition and the rate of workers on the unemployment benefit.[21] We choose to match the rate of unemployment benefit receipts, rather than the unemployment rate, because our measure of job separations taken from LEED data includes both separations into unemployment and job-to-job transitions. This means that the model-implied unemployment rate is too high relative to the observed unemployment rate. However, the rate at which workers in the model receive unemployment benefits corresponds to the same rate in the data. Figure 8(a) shows that the model closely matches the rate of employment in the services sector by age. Figure 8(b) shows that the model fits the rate of unemployment benefit receipts on average across the life-cycle, where younger workers are more likely to find themselves without work than are older workers.

5. A Pandemic Lockdown-Induced Recession Experiment

5.1. Calibration of Pandemic Shocks and Policy Responses

First, we introduce a sequence of industry-specific productivity shocks $Z_{1,t}$ and $Z_{2,t}$. These shocks reflect the effects of a strict domestic lock-down in the first quarter of the pandemic, and international border closures that persist for an additional three quarters. We assume that service sector firms are adversely affected by both the domestic lock-down and the international border closures. We allow the effects of the domestic lock-down and international border to differ, so that the size of the services sector productivity shock in the first quarter of the pandemic differs from the shocks that occur in the following three quarters. We then assume that other industry firms are affected by by the initial domestic lock-down only. Thus, non-

[21]Note that industry composition and unemployment benefit receipts are easily computed from the Markov chain transition matrix $\Gamma_{k,e,i}$ in Equation (13). This does not require us to solve the entire model for this part of the calibration.

service firm productivity declines in the first quarter of the pandemic only.

Second, we introduce a conditional wage subsidy policy indexed by policy parameters τ_w and Θ. As discussed in Section 2, a conditional wage subsidy was the primary fiscal policy response to the pandemic in New Zealand. We characterize the policy as a lump-sum payment τ_w, and a condition under which a firm becomes eligible to receive the payment. We assume the subsidy is available in the first quarter of the pandemic only, which approximates the sharp fall in subsidy receipts from July onward, as shown in Figure 3. Firms are eligible for the subsidy if they experience a sufficiently large fall in revenues relative to steady state:

$$\frac{h_{i,t}x - h_i x}{\mathbb{E}\left(J_{i,k}\right)} \leq \Theta \tag{15}$$

We scale the decline in revenues by the steady state average value of an age k worker firm $\mathbb{E}\left(J_{i,k}\right)$. We do this rather than scale by steady state revenues $h_i x$ so that the policy generates a distribution of subsidy recipients. Because the distribution over match productivity varies by age, Equation 15 implies that the probability of receiving a subsidy for a firm in industry i with a worker aged k is

$$\Pr(Subsidy|i,k) = \Pr\left(x \geq \frac{\Theta\mathbb{E}\left(J_{i,k}\right)}{h_{i,t} - h_i}\right) = 1 - \Phi_k\left(\frac{\Theta\mathbb{E}\left(J_{i,k}\right)}{h_{i,t} - h_i}\right) \tag{16}$$

where the first equality follows from the fact that $h_{i,t} < h_i$ during the pandemic, and Φ_k is the CDF over match productivity for age k workers.

We calibrate the lock-down shocks and policy parameters to match several key observations about the labor market during the pandemic in New Zealand. The details of this calibration are reported in Table 4. First, we set $Z_{1,t=1}$ and $Z_{1,t=2,3,4}$ to match the declines in service sector employment during the first two quarters of the pandemic. Second, we set $Z_{2,t=1}$ to match the decline in non-service sector employment in the first quarter of the pandemic. Figure 2 shows that relative to historical average growth rates, services employment declined by 5.2% in 2020:Q2 and by 6.7% in 2020:Q3. Non-service sector employment declined by 1.0% in 2020:Q2. To match these targets, the calibration yields a 62.6% decline in services productivity relative to steady state in the first quarter, a 6.5% decline in services productivity for the following three quarters, and a 32.1% decline in non-services productivity in the first quarter. Third, we set τ_w to match the effective size of the wage subsidy. The \$585.80 received per week under the subsidy is approximately 50% of the median weekly earnings in New Zealand. Using data from the 2019 Annual Enterprise Survey, we compute that wages and salaries are on average 18% of firms' total expenditures.[22] Thus the model-implied wage subsidy τ_w is equivalent to 9% of the median wage in the model. Finally, we set Θ so that 75% of all workers receive the wage subsidy, which is the peak coverage of the subsidy as shown in Figure 3.

[22]The Annual Enterprise Survey is provided by Statistics New Zealand and reports financial statistics from a survey of over 500,000 businesses. See https://www.stats.govt.nz/information-releases/annual-enterprise-survey-2019-financial-year-provisional.

Table 4: Pandemic Parameters and Moments

Parameter	Value	Moment	Model	Data
$Z_{1,t=1}/Z_1$	0.374	Employment Growth, Services, 2020:Q2	-0.052	-0.052
$Z_{1,t=2,3,4}/Z_1$	0.935	Employment Growth, Services, 2020:Q3	-0.067	-0.067
$Z_{2,t=1}/Z_2$	0.679	Employment Growth, Other, 2020:Q2	-0.010	-0.010
τ_w	0.113	Subsidy Size to Median Wage	0.090	0.090
Θ	-0.121	Fraction Receiving Subsidy	0.751	0.750

Notes:: Employment growth rates are computed relative to historical average growth rates.
Source: Authors' calculations using data from the Household Labour Force Survey and the Ministry of Social Development.

5.2. Evolution of the Pandemic With and Without Policy

To study the effects of the pandemic induced lockdown and policy response, we compare the evolution of the model economy to a counterfactual economy with identical productivity shocks but absent the wage subsidy policy. In Figures 9 to 12, solid blue lines illustrate the baseline economy with pandemic shocks and policy while dashed red lines illustrate the counterfactual economy absent the subsidy.

Figure 9 shows the evolution of several macroeconomic variables. In the first quarter of the pandemic, productivity in both industries declines significantly. This leads to falling output, as is shown by a decline in GDP of more than 25%.[23] With falling output and sticky wages, firm profits decline which leads to a decrease in demand for labor. As a result, aggregate employment falls by around 2.5% in the first quarter, and is around 4% below steady state in the second quarter. Falling employment is associated with a decrease in household income, which leads to a 1.25% decline in household consumption in the first period after the shock. However, the wage subsidy policy acts to dampen the macroeconomic contraction induced by the pandemic. In the counterfactual economy with no policy intervention, employment and consumption would have fallen by nearly 10% and 3%, respectively.

Figure illustrates labor market outcomes across industries during the pandemic. The service sector is more adversely affected by the pandemic than the non-service sector because it is affected by a larger initial shock and is subject to the ongoing effects of border closures. As is observed for aggregate variables, the wage subsidy significantly dampens the effects of the pandemic shocks across industries. Absent the wage subsidy, services employment would have fallen an additional 10 percent below steady state, and non-service sector employment would have fallen by a further 5 percent. The third column in Figure shows that average job separation rates change very little with the wage subsidy in place, whereas job separation rates rise significantly in the absence of the wage subsidy. In contrast, job finding rates are little changed

[23]Note, aggregate real GDP is defined as $\frac{p_1}{p}y_1 + \frac{p_2}{p}y_2$.

Figure 9: Aggregate Macroeconomic Variables During the Pandemic

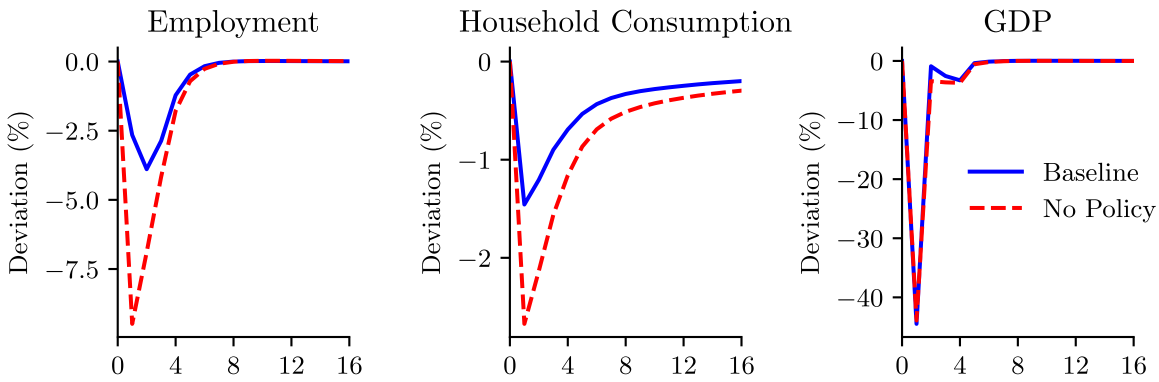
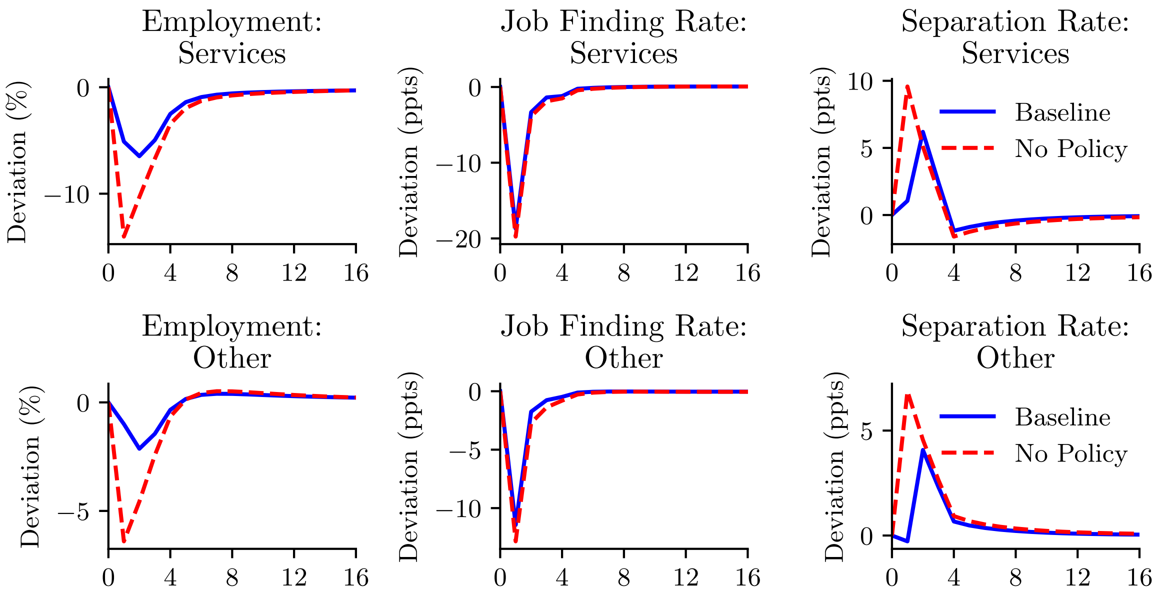


Figure 10: labor Market Outcomes During the Pandemic By Industry

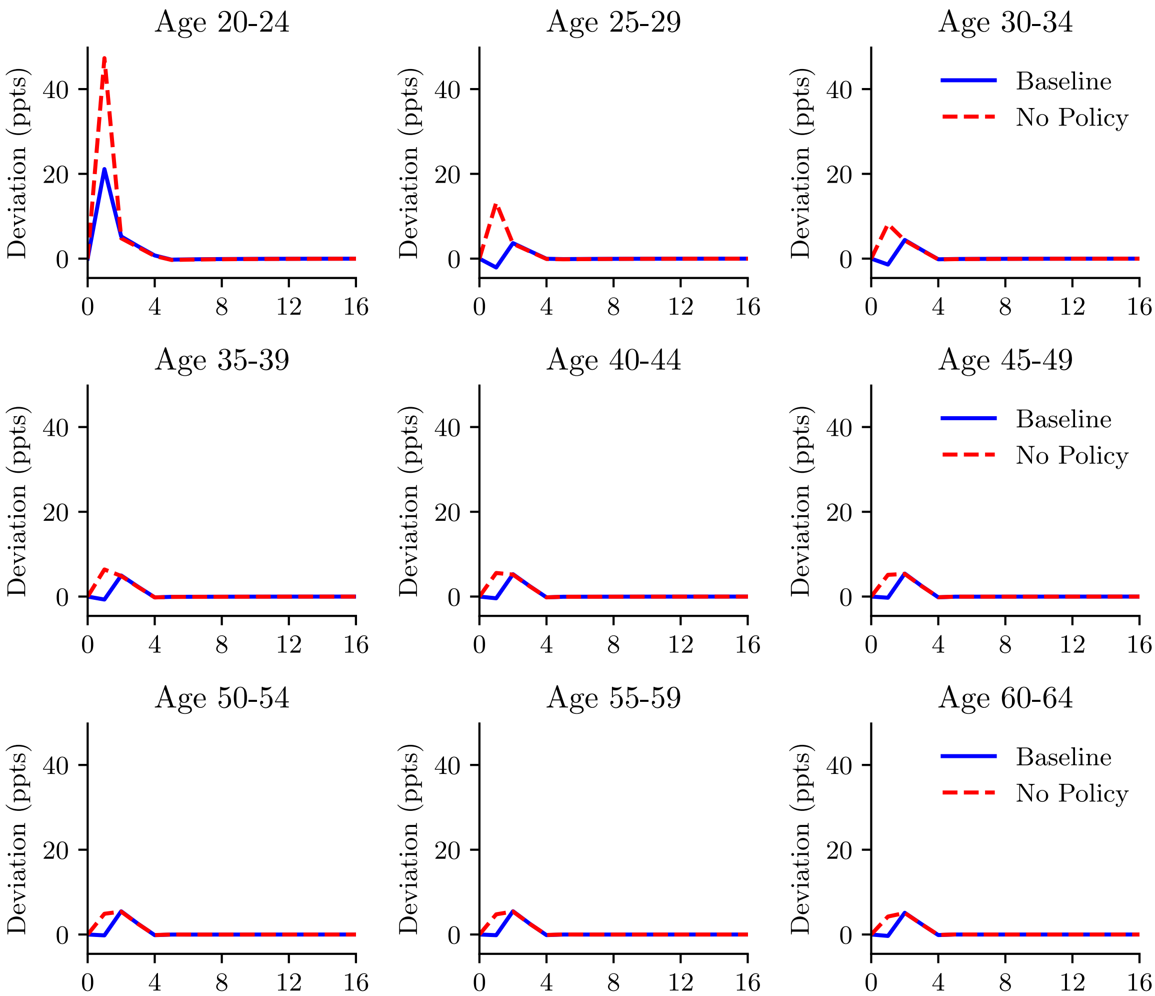


by the presence of the wage subsidy. Thus, the wage subsidy largely acts through preventing job losses, rather than by promoting firm hiring.

The effects of the pandemic are also unequally distributed across households. Figure 11 illustrates changes in job separations across the age distribution. The rate of job separations among young workers rises significantly more than for older workers. This is for two reasons. First, young workers are more likely to be employed in the service sector which faces larger pandemic shocks. Second, younger workers have lower average productivity because $\sigma_{\sigma,k}$ is increasing with age. This is associated with larger proportional decreases in firm revenues for the same sized decline in industry-level productivity Z_i.

Figure 12 shows the age distribution of consumption expenditures through the pandemic. As unemployment rises, consumption falls more for younger households than older households. This is both because average income falls further for the young, but also because young households have lower stocks of savings with which to insure against employment shocks. Although

Figure 11: Job Separation Rates by Age



unemployment also rises for older households, their large savings buffers mean that their expenditures are virtually unchanged.

In comparing outcomes across industries and age groups, we can see that the service sector and the young benefit the most from the presence of the wage subsidy. Figure shows that this is because wage subsidies are disproportionately granted to workers that are younger and employed in the service sector. The figure reports the fraction of continuing employment relationships supported by the wage subsidy in the first quarter of the pandemic. Younger and service sector workers benefit most from the wage subsidy for two reasons. First, larger productivity shocks in service sector industries lead to larger declines in revenues so that these firms are more likely to satisfy Equation 15 and receive the subsidy. Second, firms with younger workers and lower average productivity experience larger relative declines in revenue and so are also more likely to receive the wage subsidy.

Overall, the wage subsidy scheme significantly dampens the effects of the pandemic, as measured by the number of jobs saved in the first quarter of the pandemic. Table 5 shows that the wage subsidy scheme preserves up to 6.8% of steady state employment relationships,

Figure 12: Household Consumption by Age

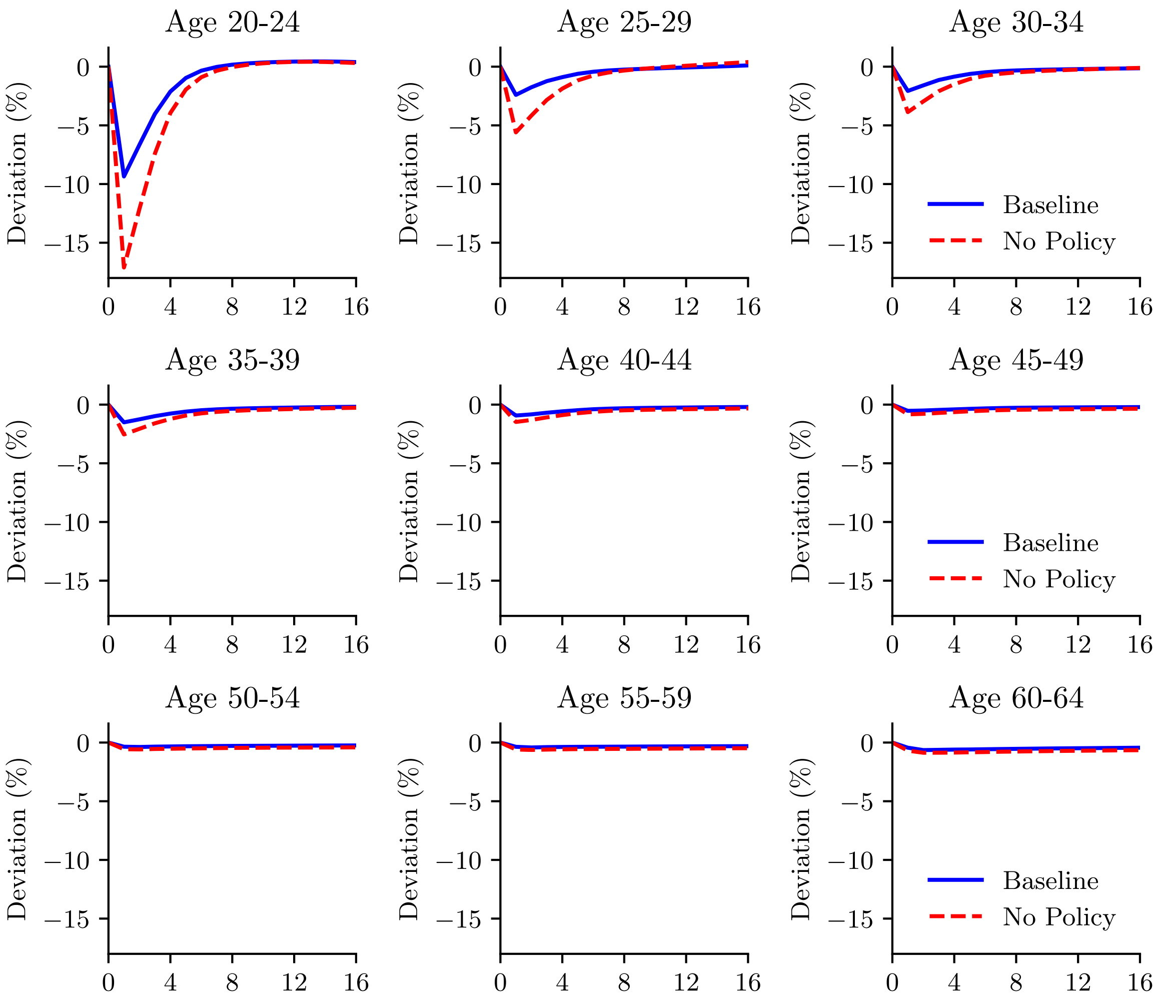
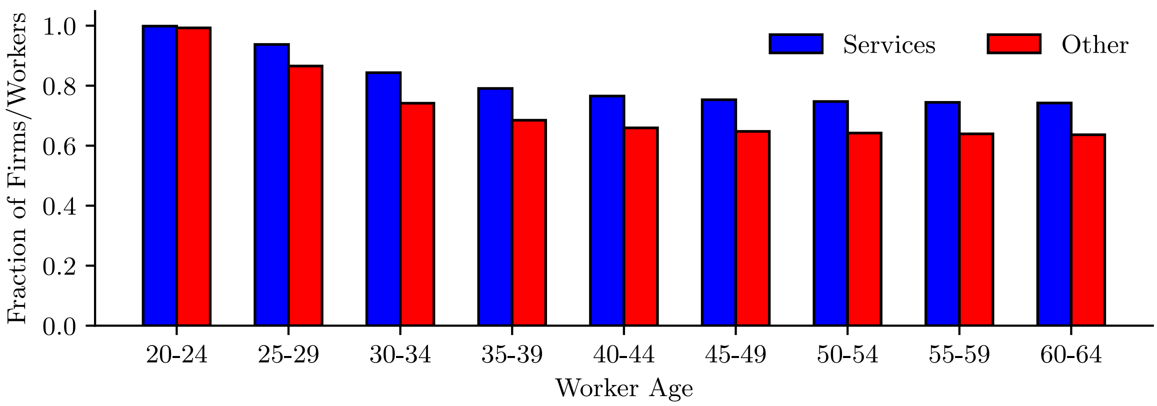


Figure 13: Wage Subsidy Receipts by Industry and Worker Age



which is the equivalent of 183,600 jobs in the New Zealand labor market.[24] As discussed above, the service sector disproportionately benefits from the wage subsidy scheme: the subsidy saves

[24]The Household labor Force Survey reports that there were approximately 2.7 million employees in New Zealand in 2019.

8.9% of service sector jobs and 5.4% of non-service sector jobs. These figures are comparable to empirical estimates of the effect of wage subsidy schemes from similar countries. For example, Bishop et al. (2020) estimate that the Australian Job Keeper wage subsidy scheme saved around 700,000 jobs, or around 5.4% of the labor force.[25]

Table 5: Jobs Saved by the Wage Subsidy Scheme

	Total Jobs	Services Jobs	Other Jobs
Jobs Saved	0.068	0.089	0.054

Notes: The number of jobs saved in each industry is computed as the difference between employment in the baseline model with the wage subsidy and the model absent the wage subsidy in the first quarter of the shock. All values are computed as fractions of steady state employment.

5.3. Evolution of the Pandemic Under Alternative Policies

While the wage subsidy scheme prevents much job loss throughout the pandemic and lockdown, it is not without cost. Table 6 reports the fiscal costs of the wage subsidy scheme per job saved. Each job saved required expenditures equivalent to approximately one quarter of average household income, nearly five times the size of the benefit paid to unemployed workers, and around one third of average household consumption expenditures.

Table 6: Costs of the Wage Subsidy Scheme

	Unemployment Benefit	Average Income	Average Consumption
Cost Per Job Saved	4.823	0.980	0.309

Notes: The number of jobs saved is computed as the difference between employment in the baseline model with the wage subsidy and the model absent the wage subsidy in the first quarter of the shock. All values computed as fractions of steady state variables reported in column headers.

The large opportunity cost of the wage subsidy scheme suggests that we also consider alternative policy responses to the pandemic. We now consider two alternative policies: a one-time lump-sum transfer, and a one-period increase in the transfer paid to unemployed workers. We study these policies since they were two of the common policy responses to the pandemic in other countries, in addition to various wage subsidy schemes. We model the effect of each alternative assuming the same sequence of pandemic shocks $\{Z_{1,t}, Z_{2,t}\}$. We also assume equal costs

[25]The Australian Bureau of Statistics reports that there were approximately 12,860,700 employees in Australia in 2020. See https://www.abs.gov.au/statistics/labor/employment-and-unemployment/labor-force-australia/latest-release.

of fiscal transfers across policies. That is, each policy alternative has the same total cost of unemployment benefits, wage subsidies, and direct transfers.[26] This ensures that comparisons across policies are made on a dollar-for-dollar basis. Table 7 reports the size of the lump-sum transfer and unemployment benefit under each policy relative to steady state unemployment benefits, average incomes, and average consumption expenditures. Under the lump-sum transfer all households receive a payment equivalent to 5% of average household income. Under the unemployment benefits policy, the benefit paid rises to more than three times the size of the benefit paid in steady state, and is 63% of average household income.

Table 7: Size of Payments Under Alternative Pandemic Policies

		Size Relative to	
	Unemployment Benefit	Average Income	Average Consumption
Lump-Sum Transfer	0.254	0.052	0.069
Higher Unemployment Benefit	3.127	0.635	0.849

Notes: The size of the lump-transfer and unemployment benefit of each policy is determined in general equilibrium subject to the constraint that the fiscal cost of redistribution under each policy alternative is equal to the fiscal cost under the baseline wage subsidy scheme. All values are computed as fractions of steady state unemployment benefits, average income, or average consumption.

Figure 14 shows the evolution of employment, consumption, and GDP during the pandemic under each of the three policy alternatives. While the wage subsidy policy directly supports the labor market, the lump-sum transfer and unemployment benefits policies do not, so employment falls significantly more under the latter two policies. In fact, under the alternative policies employment falls as much as it would have under the counter-factual with no policy intervention (see Figure 9). The path of aggregate consumption is similar under the wage subsidy and the policy with higher unemployment benefits, but falls by more under the lump-sum transfer policy. The decline in GDP is invariant to the form of the policy intervention, since output is largely determined by the industry-level productivity shocks.

Figure 15 shows the response of household consumption by age group under the three policy alternatives. For the youngest group of households, the smallest consumption decline occurs under the unemployment benefit policy. Recall that young workers earn around half as much as middle-aged workers (see Figure 7). This implies a smaller spread between the unemployment benefit and wages for younger workers than older workers. Thus, an increase in unemployment benefits represents a significant increase in expected income for the youngest households who are also the most likely to become unemployed. For older workers with higher earnings, a reduction in unemployment risk represents a larger increase in expected income than does an increase in unemployment benefits. Finally, consumption for the oldest workers hardly varies across

[26] Recall that government expenditures G_t adjust to ensure the fiscal budget constraint holds in each period, since government debt is held constant.

Figure 14: Aggregate Variables Under Alternative Policies

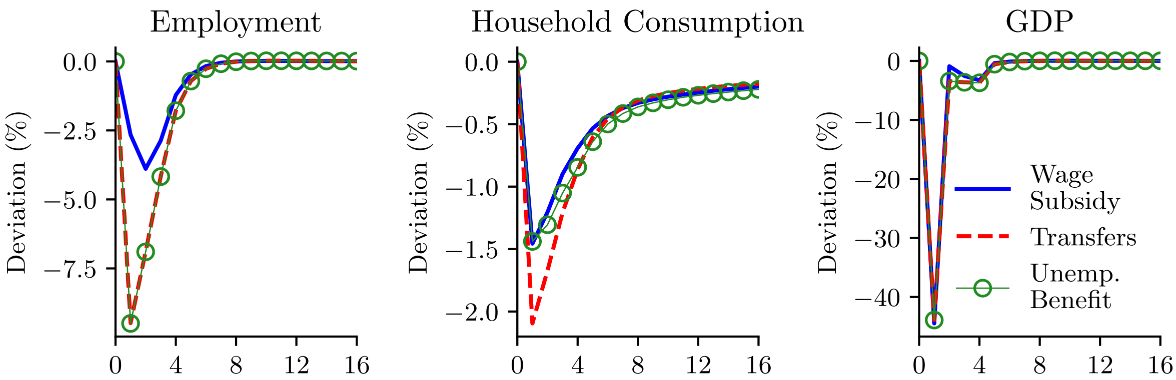
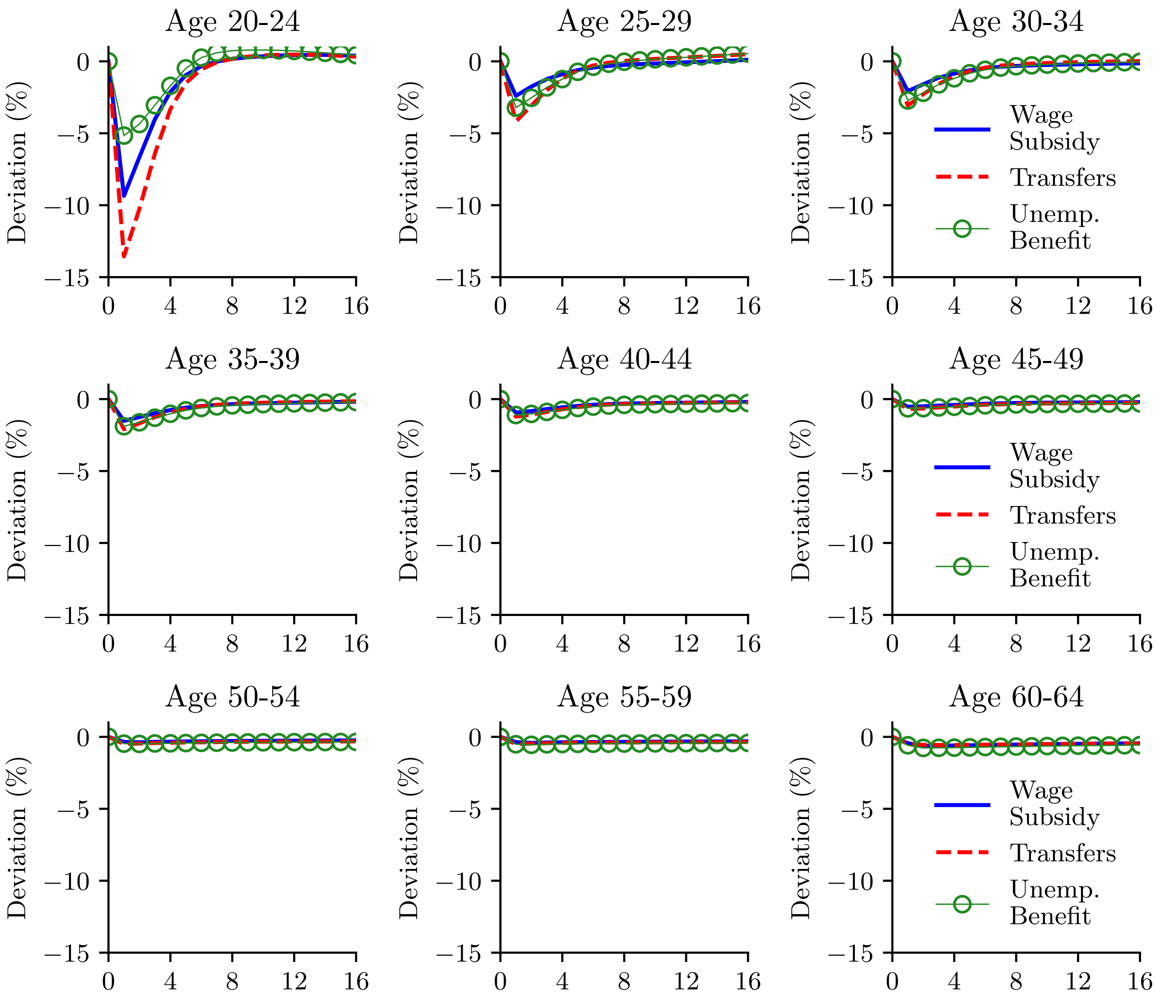


Figure 15: Consumption By Age Under Alternative Policies



policy interventions since their larger stock of savings insures them against income fluctuations. Note that the lump-sum transfer has a much smaller effect on the evolution of consumption as the payment is relatively small and much of it is directed towards older households who can comfortably smooth consumption without such payments.

5.4. Household Welfare During the Pandemic Under Alternative Policies

Finally, we study the welfare implications of the three policy interventions during the pandemic. We compute welfare gains for each policy intervention via the Consumption Equivalent Value (CEV) relative to the economy with no policy intervention. The CEV can be interpreted as the percentage gain in life-time consumption enjoyed under a particular policy intervention. We study these gains for different groups from the perspective of households in the period immediately prior to the pandemic, but who have no ability to change their behaviour before the shocks occur. These households know the value of their own state variables on the eve of the pandemic, they know the effects of the shocks and each policy intervention, and they know the distribution over possible outcomes although they do not know their employment status at the onset of the pandemic.

Table 8 reports the average CEV across all households and the fraction of households with a positive CEV under each of the three policy alternatives. These policy interventions are associated average welfare gains equivalent to between 0.15% and 0.22% of life-time consumption. While 73% of households are in favour of the wage subsidy policy, virtually every household benefits from the policies paying out lump-sum transfers and higher unemployment benefits.

Table 8: Welfare Gains from Policy Interventions During the Pandemic

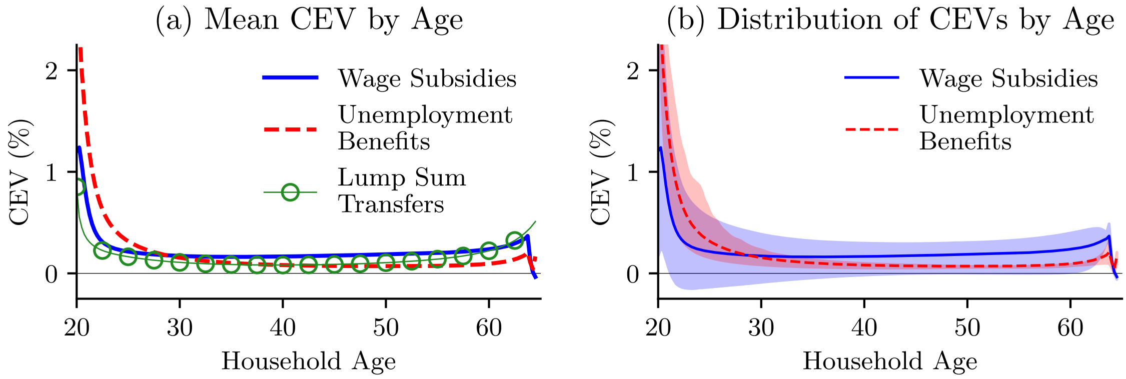
	Wage Subsidies	Lump Sum Transfers	Unemployment Benefits
Mean CEV (%)	0.223	0.155	0.206
Fraction CEV ≥ 0	0.737	1.000	0.998

Notes: Welfare gains and losses are computed using expected value functions from the perspective of households prior to the pandemic. Welfare statistics are computed for households drawn from the pre-pandemic steady state distributon.

However, there is significant variation in welfare gains across different groups of households. Figure 16(a) shows that young households enjoy the largest welfare gains from the policy that raises unemployment benefits during the pandemic. This is directly related to Figure **??**, which shows much smaller consumption fluctuations among younger households under the unemployment benefits policy. This policy raises the insurance value of unemployment, which is particularly valuable for young households that face low wages to begin with and who are more likely to become unemployed during the pandemic. The welfare benefits of all three policies fall as households age because the larger stock of assets held by older households enables them to better smooth consumption during the pandemic recession. The greater ability to smooth consumption reduces the value of policies that prevent unemployment or provide relatively small payments to these households.

Finally, 16(b) shows the 5^{th}-to-95^{th} percentiles of CEVs across age for the wage subsidy and unemployment benefits policy. A large proportion of young households under the unemploy-

Figure 16: Welfare Gains from Policy Interventions During the Pandemic by Household Age



Notes: Panel (a) shows the mean CEV for households of each age group under each of the three policies. In Panel (b), the shaded areas show the 5^{th}-to-95^{th} CEV percentiles for households in each age group under the wage subsidy policy and the unemployment benefits policy. The solid and shaded lines show the mean CEVs, as in Panel (a).

ment benefit policy enjoy larger welfare gains than the average gain under the wage subsidy. Additionally, a small proportion of young households under the wage subsidy experience welfare losses relative to the world with no policy intervention. Nearly the entire distribution of households over the age of 40 receive larger CEVs under the wage subsidy policy than under the unemployment benefits policy. These results again highlight the dispersed welfare gains of different policy responses to the pandemic. Many more young households prefer policies with direct payments, while the majority of older households prefer policies that maintain their employment relationships as is the case under a wage subsidy scheme.

6. Conclusion

In this paper, we study the macroeconomic and distributional consequences of the social and economic lockdowns implemented in response to the COVID-19 pandemic of 2020. In order to isolate the effects of lockdowns alone we consider the case of New Zealand, which imposed strict domestic lockdowns and international border closures but which endured very little exposure to the health effects of the virus itself. We build a life-cycle heterogeneous agents model with labor market frictions and multiple industries, calibrated to the New Zealand economy. We then study the dynamic response of the model to a series of industry-level negative productivity shocks, which mimic the effects of a lockdown on production and the demand for labor. The calibrated lockdown shocks generate the same declines in model employment as observed in New Zealand data over the course of the 2020 pandemic, suggesting an appropriate characterization of the effect of these shocks. Finally, we model the large wage subsidies paid to firms in New Zealand during the pandemic and study both the aggregate and cross-sectional effects of this unprecedented fiscal intervention.

We find that pandemic-induced lockdowns disproportionately affect both service sector and young workers. Larger declines in service sector productivity result in larger increases in job separations in that industry, where young workers are more likely to be employed. Additionally, lower initial productivity among the youth in general leads employers to shed young workers more quickly than older workers. In the presence of a no-borrowing constraint and with young workers having had less time to accumulate savings, consumption is much more volatile for young households during the pandemic than it is for older households with the resources to self-insure against employment shocks.

Using counterfactual model outcomes, we show that the wage subsidies offered by the New Zealand government prevented a large number of job losses during the lockdown. Moreover, we find that this subsidy disproportionately benefited service sector and young workers; those who were most affected by lockdowns in the first place. The varied cross-sectional effects of the subsidy are due to the conditional nature of its implementation: firms were only eligible for the wage subsidy if they experienced a sufficiently large decline in revenue during the initial lockdown period. In the model, firms in the service-sector and those that employ young workers experience a disproportionately large decline in revenues, which leaves them more likely to be eligible for the wage subsidy.

Finally, we study the welfare consequences of the wage subsidy policy in comparison to other possible fiscal interventions. We consider policies with the same fiscal outlays as the wage subsidy policy. The first policy pays a lump sum transfer to all households, while the second policy raises unemployment benefits. We find that young workers are better off under a policy that raises unemployment benefits. This is because the higher insurance value of unemployment for those who are most likely to become unemployed during a lockdown is more valuable than the increased probability of retaining a job under the wage subsidy policy.

While our model captures many rich features of the household life-cycle and exposure to the labor market, we eschew other model features that may also be important for understanding the impact of the COVID-19 Pandemic. First, our search model of the labor market does not allow for long-term labor market scarring. The effects of labor market scarring may increase the benefits of wage subsidy policies that prevent the onset of long unemployment spells. Second, for tractability we assume that households only having access to a liquid asset to facilitate saving. However, the large literature studying HANK models suggests that even wealthy households are sensitive to an increase in labor market risk when much of their wealth is held in illiquid assets (see Graves, 2020). Introducing a second illiquid asset would also likely amplify the welfare benefits of fiscal interventions during the pandemic, since even wealthy households would stand to benefit from these income-smoothing policies.

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