Bringing Back the Jobs Lost to Covid-19: The Role of Fiscal Policy*

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This version: February 23, 2021

Abstract

Covid-19 induced job losses occurred predominantly in industries with intensive worker-client interaction as well as in pink-collar and blue-collar occupations. We study the ability of fiscal policy to stabilize employment by occupation and industry during the Covid-19 crisis. We use a multi-sector, multi-occupation macroeconomic model and investigate different fiscal policy instruments that help the economy recover faster. We show that fiscal stimuli foster job growth for hard-hit pink-collar workers, whereas stimulating blue-collar job creation is more challenging. Only a cut in labor income taxes generates a substantial number of blue-collar jobs.

Keywords: Covid-19, Fiscal Policy, Composition of Employment, Occupations, Industries, Heterogeneity

JEL classification: E62, E24, J21, J23

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1 Introduction

Job losses in the Covid-19 recession stand out in comparison to those in other recessions in two ways. First, the Covid-19 downturn is enormous, and it unfolded at unprecedented speed. From February to April 2020, total private employment fell by more than 22 million jobs, and the unemployment rate skyrocketed from 3.5% to 14.8%. One year after the start of the pandemic, employment remained nearly ten million jobs below pre-pandemic levels, which is more than the peak-to-trough gap from the Great Recession. Second, it is an unusual mix of workers who are struck by job losses. In a typical recession, job losses are concentrated in construction and manufacturing industries and in blue-collar occupations (Hoynes, Miller, and Schaller, 2012). During the Covid-19 recession, job losses have occurred to a great extent in sectors with a high intensity of worker-client interaction. Between February and April 2020, over 10 million jobs have been lost in "retail trade" and "leisure and hospitality" industries alone. The most affected major occupation group is service occupations, with an employment drop of one third from February to April 2020. In general, so-called pink-collar workers (workers in sales and service occupations) have suffered most, followed by blue-collar workers who suffered from heavy job losses, too, as in any downturn.[1] In contrast, white-collar workers were affected relatively mildly.

While there is no role for aggregate demand management as long as public-health measures bring down the economy's potential output, aggregate demand management is relevant when restrictions are relaxed such that potential output can return toward its pre-crisis level. Then, a fiscal stimulus can be a tool to accelerate the recovery of actual output and employment. When this is possible, economic policy should not only concentrate on pushing up the total number of jobs but should also be concerned with the industry mix and –in particular– the occupation mix of employment to avoid excessive losses of industry-specific and occupation-specific human capital. Kambourov and Manovskii (2009) show that displaced workers' future earnings losses are three times larger when they are unable to find a job in their initial occupation. The costs of switching occupations are estimated to be as high as several annual earnings for switches between major occupation groups (see Artuç and McLaren, 2015, and Cortes and Gallipoli, 2018). Moreover,

[1] Some commentators referred to the Covid-19 recession as a "pink-collar recession" (Celina Ribeiro in The Guardian, May 23, 2020; Nancy Wang on Forbes, May 24, 2020). Due to the high share of women in pink-collar occupations and sectors with a high intensity of worker-client interaction, Covid-induced job losses for women have been much higher than during typical recessions (Alon, Doepke, Olmstead-Rumsey, and Tertilt, 2020).

the returns to occupational tenure are found to be almost as large as the total returns to labor-market experience and to exceed the returns to firm or industry tenure, see, e.g., Shaw (1984), Kambourov and Manovskii (2009), and Sullivan (2010). This evidence suggests that stabilization policy can reduce the economic costs of the Covid-19 pandemic if, during the recovery, fiscal policy promotes job creation in the occupation groups hit hardest by the crisis. In this paper, we conduct a model-based analysis of the effectiveness of different fiscal-policy measures in pursuing this goal.

To clarify the scope of our analysis, it is helpful to apply Olivier Blanchard's taxonomy of the roles of fiscal policy in the Covid-19 crisis.[2] According to Blanchard, the first role of fiscal policy is infection-fighting, i.e., to spend much on testing and create incentives for firms to produce necessary medical equipment. The second role is disaster relief, i.e., to provide transfers and loans to households and firms in order to avoid excessive hardship and bankruptcies. The much-discussed extensions of unemployment benefits also belong in this category. The third role is aggregate demand management when infections are under control and restrictions can be relaxed. We focus on the third role (aggregate demand management) and, to isolate this role, we assume that policy is or has been successful in the first two roles. Our model has no interaction between infections and economic activity (i.e., infections are under control in the model) and abstracts from consumption heterogeneity or bankruptcies (i.e., disaster relief is successful in the model).[3]

To study the effects of fiscal-policy stimulus in the Covid-19 recovery, we use a multi-sector, multi-occupation New Keynesian business-cycle model. We distinguish between two large sectors of the economy and three broad occupation groups. Following Kaplan, Moll, and Violante (2020), we differentiate between a "social" sector that comprises industries with high physical proximity between clients and workers, such as retail trade and hospitality, and a "distant" sector where less face-to-face contact is required. Our broad occupation groups are, first, white-collar occupations such as management, professional, and office occupations, second, blue-collar occupations such as production or construction occupations, and, third, service and sales ("pink-collar") occupations. Our model generates heterogeneity in occupational employment dynamics as a consequence of i) a

[2]See, for example, Olivier Blanchard: Designing the fiscal response to the Covid-19 pandemic. `https://www.piie.com/blogs/realtime-economic-issues-watch/designing-fiscal-response-covid-19-pandemic`

[3]For model-based analyses of the interaction between infections and economic activity, see, for example, Acemoglu, Chernozhukov, Werning, and Whinston (2020), Eichenbaum, Rebelo, and Trabandt (2020), and Krueger, Uhlig, and Xie (2020).

composition effect due to heterogeneous employment changes across sectors with different average occupation mixes and ii) changes in the occupation mix within sectors due to differences in the substitutability with capital services across occupations (similar to Autor and Dorn, 2013, and Bredemeier, Juessen, and Winkler, 2020). In particular, labor provided by blue-collar occupations is, on average, more easily substitutable with capital than labor provided by white-collar and pink-collar occupations.

We calibrate the model to the U.S. economy and expose it to a pandemic shock that generates employment losses by industry and occupation, as seen during the Covid-19 crisis. Hence, employment falls particularly sharply in the social sector as well as in blue-collar and pink-collar occupations. We then perform the following policy experiments: One year after the pandemic shock hits the economy, expansionary fiscal policy supports the economic recovery.[4] We consider a variety of fiscal stimuli, both spending-based and tax-based. We further differentiate between spending packages that differ in how strongly they are directed toward a specific sector as well as between capital and labor income tax cuts.

Our results show that, in general, expansionary fiscal-policy measures promote employment growth disproportionately in the social sector and in pink-collar occupations, which counteracts the substantial losses these groups experience due to the pandemic. By contrast, most fiscal stimulus measures exert only a low push on blue-collar employment and are hence ineffective in promoting the recovery for this group of workers. Comparing the different fiscal stimulus measures, our results show that directing spending strongly toward one of the sectors does not impact too strongly on the composition of the created jobs due to counteracting changes in the sectoral composition of private demand and the occupation mix within sectors. Even a spending expansion directed strongly toward the distant sector fosters blue-collar employment the least. The measure that quickens the recovery in blue-collar work most strongly after the imminent Covid-19 crisis is a cut in tax rates on labor income.

Our paper contributes to the literature on fiscal policy during the Covid-19 crisis. Bayer, Born, Luetticke, and Müller (2020) quantify the effectiveness of disaster relief in limiting the economic fallout from the Covid-19 pandemic by computing multipliers for the transfer component of the

[4]The time gap between the shock hitting the economy and the stimulus measures taking effect reflects aggregate demand management being ineffective in the first phases of the pandemic.

CARES Act in an estimated heterogenous-agents New Keynesian model. Likewise, Faria-e-Castro (2020) uses a two-agent New Keynesian model to compute the effectiveness of different types of fiscal policy instruments in cushioning the immediate effects of the Covid-19 shock, including a quantification of the impact of the CARES Act. Our paper complements these works in that it analyzes the impact of different fiscal instruments that support aggregate demand once potential output returns toward its pre-crisis level. Moreover, our focus is on how fiscal policy affects employment possibilities of workers, which are, in no small degree, determined by the labor-market situation in the worker's industry and occupation. Bredemeier, Juessen, and Winkler (2020) provide evidence of differences in the impact of government spending shocks on pink-collar relative to blue-collar employment and develop a business-cycle model that can explain these heterogeneous occupational employment dynamics. This paper extends our previous work in two important dimensions. First, we investigate the effects of a variety of fiscal policy instruments – different spending-based programs as well as cuts in labor and capital taxes. Second, we conduct a model-based analysis of potential fiscal policy measures in the recovery after a pandemic shock, which we calibrate to mimic the labor market during the Covid-19 crisis.[5]

The remainder of this paper is organized as follows. In Section 2, we present the model, its calibration, and how we model the pandemic crisis. In Section 3, we present results on the impacts of a variety of fiscal stimulus measures, which are aimed at helping the economy recover, on employment by occupation and sector. Besides their employment effects, we also investigate the impact of these policy measures on the income distribution across worker groups. Section 4 concludes.

2 Model

We consider a two-sector economy consisting of firms, households, and the government. We will calibrate the model such that there is a "social" sector and a "distant" sector, following the classification by Kaplan, Moll, and Violante (2020). Firms in each sector produce differentiated goods under monopolistic competition and face costs of price adjustment. Production inputs are

[5] In general, our paper is related to the literature on the distributional consequences of fiscal policy, see, amongst others, Anderson, Inoue, and Rossi (2016), Giavazzi and McMahon (2012), Johnson, Parker, and Souleles (2006), Misra and Surico (2014), Brinca, Holter, Krusell, and Malafry (2016), Kaplan and Violante (2014), and McKay and Reis (2016).

capital services and three types of occupational labor – pink-collar, blue-collar, and white-collar labor. The output of each sector is used for investment, consumption, and government spending. Households are families whose members differ by occupation and can work in either sector. The government consists of a monetary and a fiscal authority. The monetary authority sets the short-term nominal interest rate. The fiscal authority collects income taxes, issues short-term government bonds, pays transfers, and purchases goods from both sectors for government consumption.

Before we describe the model in detail, we highlight the decisive factors through which the model can generate heterogeneity in the responses of employment to economic shocks. First, sectors can be affected differently by economic shocks leading to different employment responses across sectors. This leads to heterogeneity in the responses of occupational employment through a *composition effect* as long as the occupation mix of employment differs across sectors. Consider, for example, a demand shock that boosts economic activity mainly in the social sector, which employs a disproportionate share of pink-collar workers (think about a fiscal stimulus targeted directly toward the social sector). For a given occupation mix within sectors, the associated employment boom brings about predominantly pink-collar jobs since pink-collar jobs are concentrated in the social sector. Of course, the strength of this channel depends on how differently sectoral employment responds to the shock. If, in our example, changes in private demand weaken the demand stimulus targeted toward the social sector considerably, employment in the social sector may not increase significantly more strongly than in other sectors.

A second channel that can generate heterogeneity in the employment responses to economic shocks relates to *capital-labor substitution*. In our model, there is a change in the occupation mix of employment within sectors when we allow for differences across occupations in the short-run substitutability between labor and capital services, that is, the stock of physical capital times the intensity with which it is used. In particular, we build on the notion that labor provided by blue-collar occupations is, on average, more easily substitutable with capital services than labor provided by pink-collar and white-collar occupations (similar to Autor and Dorn, 2013). To understand how this can lead to changes in the occupation mix of employment, consider a positive shock to aggregate demand again, now affecting both sectors equally. In response to the shock, firms in both sectors demand more factor inputs to meet increased product demand, which puts upward pressure on factor costs. Given the fact that the short-run supply of capital services is relatively more elastic compared to the supply of labor, factor costs change in favor of capital use compared to labor. Therefore, firms raise their demand for capital services more than their demand for labor. The disproportionate surge in capital usage lowers the marginal productivity of its closer substitute, blue-collar employment, relative to pink-collar or white-collar employment. Thus, firms change their occupation mix in favor of pink-collar and white-collar work, employing now a higher share of pink-collar workers than before (see Bredemeier, Juessen, and Winkler, 2020). Of course, a shock that directly affects the relative costs of labor in a way such that labor becomes cheaper relative to capital (for example, a cut in labor income taxes), will lead to the opposite result. In this case, blue-collar workers will benefit disproportionately as firms substitute away from capital services toward labor.

The occupation mix within a sector has implications for the overall employment effects of fiscal policy within a sector. The less easily labor can be substituted by capital within an industry, the higher will be the job multiplier in the industry. This is the case in the social sector, which employs a disproportionate share of pink-collar workers. By contrast, in industries that employ relatively many blue-collar workers, additional government purchases lead to comparatively moderate employment boosts as firms in such sectors meet the increased demand by raising their use of capital services predominantly.

Three model features are necessary for our mechanism and hence the main results. First, the short-run supply elasticity of capital services is required to be larger than the supply elasticity of labor. Second, elasticities of substitution with capital services have to be heterogenous across occupations, with blue-collar labor being the closest substitute to capital services and pink-collar labor being the closest complement to capital services. Third, the mechanism relies on a feature that transmits fiscal expansions to the labor market in the form of a rightward shift of the labor *demand* schedule – in our case, this feature is price rigidity.[6]

Our model incorporates a few additional features that improve the model's quantitative perfor-

[6]There is empirical evidence for all three features. First, the elasticity of capital utilization is usually estimated to be considerably larger than Frisch labor supply elasticities (see, for example, Schmitt-Grohé and Uribe, 2012, Smets and Wouters, 2007, or Christiano, Eichenbaum, and Evans, 2005). Second, occupation-specific elasticities of capital-labor substitution are usually understood to depend on the type of tasks workers perform in different occupations. Autor and Dorn (2013) emphasize the high share of routine-manual tasks performed by blue-collar occupations implying a large elasticity of capital-labor substitution in this occupation group. Third, evidence for sluggish reactions of prices to economic shocks abounds (e.g., Christiano, Eichenbaum, and Evans, 2005, Bils and Klenow, 2004).

mance. Labor adjustment costs serve as a stand-in for rigidities in hiring and firing stemming from the importance of worker-firm matches, union power, and related aspects. They are responsible for sluggish responses of employment to economic shocks. We assume these costs to be sector-specific, and, in our calibration, they are higher in the distant sector. In Bredemeier, Juessen, and Winkler (2020), this assumption allows matching the delayed response to government spending shocks of employment in sectors that employ relatively many blue-collar workers. Finally, we incorporate direct feedback to fiscal policy in the monetary policy rule. This model feature is consistent with evidence that U.S. monetary-policy rates systematically fall in response to fiscal expansions.[7] Monetary accommodation results in a model-implied fiscal multiplier of 0.82, which is well within the range of most empirical estimates (see Ramey, 2016, for an overview). Furthermore, we believe that monetary accommodation describes monetary policy during and in the aftermath of the Covid-19 crisis rather well. It does not appear reasonable to assume that, in the near term, monetary policy will lean against a fiscal expansion that aims to help the economy recover faster. In sensitivity analyses, we document that these additional model features, while quantitatively relevant, are innocuous for our qualitative results.

We expose our model economy to a pandemic shock. Following Eichenbaum, Rebelo, and Trabandt (2020), we use stochastic wedges to construct a pandemic scenario that matches empirical job losses by sector and occupation group during the Covid-19 crisis in 2020. The wedges combine aspects of both supply and demand disturbances, in line with the evidence by Brinca, Duarte, and Faria-e-Castro (2020) and the theoretical results by Guerrieri, Lorenzoni, Straub, and Werning (2020) and Baqaee and Farhi (2021). In particular, we incorporate stochastic wedges between producer prices and the total consumer cost of a good as well as between firms' labor costs and workers' effective net labor income. The price wedge in the social sector can be interpreted as the additional cost associated with trading this sector's output in times of social distancing. The labor market wedges can be interpreted as the extra cost required to provide labor services during the pandemic. These costs are plausibly heterogeneous across occupations since occupations differ considerably in terms of work-from-home possibilities (see, e.g., Dingel and Neiman, 2020).

[7] See, Edelberg, Eichenbaum, and Fisher (1999), Mountford and Uhlig (2009), Fisher and Peters (2010), Ramey (2016), Bredemeier, Juessen, and Schabert (2020), and D'Alessandro, Fella, and Melosi (2019).

2.1 Model description

Households. There is a continuum of infinitely-lived households, with mass normalized to one. Each household supplies pink-collar, blue-collar, and white-collar labor to both sectors. Household members are not allowed to switch their occupation, in line with empirical evidence that occupation switches are associated with substantial costs (see, e.g., Kambourov and Manovskii, 2009, Artuç and McLaren, 2015, Cortes and Gallipoli, 2018) and occur rarely (see, e.g., Moscarini and Thomsson, 2007, Fujita and Moscarini, 2013, Foote and Ryan, 2014). We assume a unitary household that cares about its total consumption level of a composite good (consisting of goods of both sectors) and receives disutility from all types of labor – pink-collar labor, n_t^p, blue-collar labor, n_t^b, and white-collar labor, n_t^w. With this modeling assumption, our analysis should be understood as a positive analysis. At the same time, our model is not supposed to allow a normative analysis of the distributional effects of stabilization policy.

Each household maximizes lifetime utility

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t, n_t^p, n_t^b, n_t^w), \tag{1}$$

where $\beta \in (0,1)$ is the households' discount factor and c_t is consumption of a composite good, defined as an aggregate of consumption of the sector-1 good, $c_{1,t}$, and consumption of the sector-2 good, $c_{2,t}$, with substitution elasticity $\mu > 0$,

$$c_t = \left(\zeta^{\frac{1}{\mu}} \cdot (c_{1,t})^{\frac{\mu-1}{\mu}} + (1-\zeta)^{\frac{1}{\mu}} \cdot (c_{2,t})^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}} . \tag{2}$$

Given a decision on the composite consumption good c_t, the household allocates optimally the expenditure on consumption of good 1 and good 2 by minimizing total expenditures $(1+\wedge_{1,t})p_{1,t}c_{1,t}+(1+\wedge_{2,t})p_{2,t}c_{2,t}$, subject to (2), where $p_{1,t}$ and $p_{2,t}$ are the prices of the sectoral goods and $\wedge_{1,t}$ and $\wedge_{2,t}$ are good-specific wedges that follow exogenous stochastic processes with mean zero. These wedges, among other wedges discussed below, allow us to capture a pandemic downturn in our model. In particular, the pandemic-induced sector-specific collapses in demand will be triggered by sector-specific increases in the price wedges.

Following Horvath (2000), we assume that members of each household supply labor to firms in both sectors according to

$$n_t^o = \left((\aleph^o)^{-\frac{1}{\omega}} \cdot \left(n_{1,t}^o\right)^{\frac{1+\omega}{\omega}} + (1-\aleph^o)^{-\frac{1}{\omega}} \cdot \left(n_{2,t}^o\right)^{\frac{1+\omega}{\omega}} \right)^{\frac{\omega}{1+\omega}}, \quad \text{for} \quad o = p, b, w. \tag{3}$$

The parameter $\omega > 0$ controls the degree of labor mobility across sectors. For $\omega \to \infty$, labor can be freely reallocated and all sectors pay the same hourly wage at the margin. For $\omega < \infty$ there is a limited degree of sectoral labor mobility and sectoral wages are not equalized. Given a decision on n_t^p, n_t^b, and n_t^w the household allocates optimally the supply of labor to sectors 1 and 2 by maximizing, for $o = p, b, w$, real wage income $(1 - \wedge_t^o)\left(w_{1,t}^o n_{1,t}^o + w_{2,t}^o n_{2,t}^o\right)$, subject to (3), where $w_{1,t}^o$ and $w_{2,t}^o$ are sector-specific real wages for white-collar, blue-collar, and pink-collar labor. The term $\wedge_t^o$ is an occupation-specific wedge that follows an exogenous stochastic process with mean zero. In our model, the pandemic-induced occupation-specific employment losses will be matched by changes in occupation-specific labor wedges.

Following Jaimovich and Rebelo (2009), the period utility function $u(c_t, n_t^p, n_t^b, n_t^w)$ takes a form that allows to parameterize the wealth effect on labor supply:

$$\frac{\left(c_t - \left(\frac{\Omega^p}{1+1/\eta}(n_t^p)^{1+1/\eta} + \frac{\Omega^b}{1+1/\eta}(n_t^b)^{1+1/\eta} + \frac{\Omega^w}{1+1/\eta}(n_t^w)^{1+1/\eta}\right) x_t\right)^{1-1/\sigma} - 1}{1 - 1/\sigma}, \tag{4}$$

where $\sigma > 0$ is the intertemporal elasticity of substitution in consumption, $\Omega^p > 0$, $\Omega^b > 0$, and $\Omega^w > 0$ are scale parameters, x_t is a weighted average of current and past consumption evolving over time according to

$$x_t = c_t^\chi x_{t-1}^{1-\chi}, \tag{5}$$

$\chi \in (0, 1]$ governs the wealth elasticity of labor supply, and $\eta > 0$ is the Frisch elasticity of labor supply in the limiting case $\chi \to 0$. In this case, there is no wealth effect on labor supply and preferences are of the type considered by Greenwood, Hercowitz, and Huffman (1988).

The household's period-by-period budget constraint (in real terms) is given by

$$\begin{aligned} c_t + \frac{(1+\wedge_{1,t})p_{1,t}}{p_t} i_{1,t} + \frac{(1+\wedge_{2,t})p_{2,t}}{p_t} i_{2,t} + b_t = \\ (1+r_{t-1})\frac{b_{t-1}}{\pi_t} + (1-\tau_t^k)\left(r_{1,t}^k \tilde{k}_{1,t} + r_{2,t}^k \tilde{k}_{2,t}\right) + T_t + d_t \\ + (1-\tau_t^n)\left[w_t^p n_t^p + w_t^b n_t^b + w_t^w n_t^w\right] \\ - \frac{(1+\wedge_{1,t})p_{1,t}}{p_t} e(u_{1,t})k_{1,t-1} - \frac{(1+\wedge_{2,t})p_{2,t}}{p_t} e(u_{2,t})k_{2,t-1}\,, \end{aligned} \tag{6}$$

where $p_t = \left(\zeta \cdot [(1+\wedge_{1,t})p_{1,t}]^{1-\mu} + (1-\zeta)\cdot[(1+\wedge_{2,t})p_{2,t}]^{1-\mu}\right)^{1/(1-\mu)}$ is the price of the composite good c_t, $i_{s,t}$ is investment into physical capital in sector s (where $s = 1, 2$), b_{t-1} is the beginning-of-period stock of real government bonds, τ_t^n is the labor tax rate, τ_t^k is the capital tax rate, $\tilde{k}_{s,t}$ are capital services in sector s, $r_{s,t}^k$ is the sector-specific rental rate of capital services, $k_{s,t-1}$ denotes the beginning-of-period capital stock in sector s, $u_{s,t}$ is capital utilization in sector s, $e(u_{s,t})$ are the costs of capital utilization in sector s, T_t are government transfers, $d_t = d_{1,t}+d_{2,t}$ are dividends from the ownership of firms in both sectors, r_t is the nominal interest rate, $\pi_t = p_t/p_{t-1}$ is consumer price inflation, and $w_t^o = \left(\aleph^o \cdot ((1-\wedge_t^o)w_{1,t}^o)^{1+\omega} + (1-\aleph^o)\cdot((1-\wedge_t^o)w_{2,t}^o)^{1+\omega}\right)^{1/(1+\omega)}$ is the aggregate real wage for occupation $o = p, b, w$.

Following Ramey and Shapiro (1998), we assume that capital goods for a particular sector must be produced within that sector. Thus, the capital stock in each sector evolves according to

$$k_{s,t} = (1-\delta)k_{s,t-1} + \left(1 - \frac{\kappa_i}{2}\left(\frac{i_{s,t}}{i_{s,t-1}} - 1\right)^2\right) i_{s,t}\,, \quad s = 1, 2\,, \tag{7}$$

where $\delta \in (0,1)$ is the capital depreciation rate and $\frac{\kappa_i}{2}\left(i_{s,t}/i_{s,t-1} - 1\right)^2$ represents investment adjustment costs with $\kappa_i \geq 0$.

Households choose capital utilization rates $u_{s,t}$, which transform physical capital in sector s into capital services $\tilde{k}_{s,t}$ according to $\tilde{k}_{s,t} = u_{s,t}k_{s,t-1}$. Costs of capital utilization are given by

$$e(u_{s,t}) = \delta_1(u_{s,t} - 1) + \frac{\delta_2}{2}(u_{s,t} - 1)^2\,, \quad s = 1, 2\,,$$

which implies the absence of capital utilization costs at the deterministic steady state in which capital utilization is normalized to $u_s = 1$. The elasticity of capital utilization with respect to the rental rate of capital, evaluated at the steady state, is given by $\Delta = \delta_1/\delta_2 > 0$. As capital is predetermined, Δ corresponds to the short-run elasticity of the supply of capital services.

Households choose quantities (c_t, x_t, b_t, $k_{s,t}$, $i_{s,t}$, $u_{s,t}$, n_t^b, n_t^p, and n_t^w), taking as given the set of prices (w_t^p, w_t^b, w_t^w, p_t, $p_{s,t}$, $r_{s,t}^k$, and r_t), dividends (d_t), transfers (T_t), taxes (τ_t^n, τ_t^k), and wedges ($\wedge_{s,t}$, $\wedge_t^b$, $\wedge_t^p$, $\wedge_t^w$) to maximize (1) subject to (5), (6) and (7). First-order conditions can be found in the Appendix.

Firms. Each sector $s = 1, 2$ produces a final good and a continuum of intermediate goods indexed by j, where j is distributed over the unit interval. Each intermediate good is produced by a single firm. There is monopolistic competition in the markets for intermediate goods. Final goods firms in each sector use intermediate goods $y_{j,s,t}$, taking as given their price $p_{j,s,t}$, and sell the output $y_{s,t}$, at the competitive price $p_{s,t}$. The production function of the sector-s final good is $y_{s,t} = \left(\int_0^1 y_{j,s,t}^{(\epsilon-1)/\epsilon} di\right)^{\epsilon/(\epsilon-1)}$, where $\epsilon > 1$ is the elasticity of substitution between different varieties.

Firm j in sector s produces its output $y_{j,s,t}$ using capital services $\tilde{k}_{j,s,t}$, three types of labor, blue-collar labor $n_{j,s,t}^b$, pink-collar labor $n_{j,s,t}^p$, and white-collar labor $n_{j,s,t}^w$, and the following nested normalized CES production technology:

$$y_{j,s,t} = y_{j,s} \cdot \left(\upsilon_s \cdot \left(\frac{v_{j,s,t}^p}{v_{j,s}^p} \right)^{\frac{\iota-1}{\iota}} + (1-\upsilon_s) \cdot \left(\frac{n_{j,s,t}^w}{n_{j,s}^w} \right)^{\frac{\iota-1}{\iota}} \right)^{\frac{\iota}{\iota-1}}, \tag{8}$$

where $v_{j,s,t}^p$ is a normalized CES bundle of $v_{j,s,t}^b$ and pink-collar labor, given by

$$v_{j,s,t}^p = v_{j,s}^p \cdot \left(\alpha_s \cdot \left(\frac{v_{j,s,t}^b}{v_{j,s}^b} \right)^{\frac{\theta-1}{\theta}} + (1-\alpha_s) \cdot \left(\frac{n_{j,s,t}^p}{n_{j,s}^p} \right)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}},$$

where $v_{j,s,t}^b$ is, in turn, a normalized CES bundle of capital services and blue-collar labor:

$$v_{j,s,t}^b = v_{j,s}^b \cdot \left(\gamma_s \cdot \left(\frac{\tilde{k}_{j,s,t}}{\tilde{k}_{j,s}} \right)^{\frac{\phi-1}{\phi}} + (1-\gamma_s) \cdot \left(\frac{n_{j,s,t}^b}{n_{j,s}^b} \right)^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}}.$$

The parameter $\phi > 0$ captures the elasticity of substitution between capital services and labor in the representative blue-collar occupation, the parameter $\theta > 0$ captures the elasticity of substitution between capital services and labor in the representative pink-collar occupation, and the parameter ι captures the elasticity of substitution between capital services and labor in the representative white-collar occupation. The parameters $\upsilon_s \in (0, 1)$, $\alpha_s \in (0, 1)$, and $\gamma_s \in (0, 1)$ reflect factor intensities in production. The normalization of the CES production technology allows to disentangle the factor intensities υ_s, α_s, and γ_s from the elasticities of substitution ι, ϕ, and θ (see, e.g., León-Ledesma, McAdam, and Willman, 2010).

The firm chooses $\tilde{k}_{j,s,t}$, $n^w_{j,s,t}$, $n^b_{j,s,t}$, and $n^p_{j,s,t}$ to minimize its costs (deflated by the consumer price index p_t)

$$\begin{aligned} \mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \Big\{ & w^b_{s,t} n^b_{j,s,t} + w^p_{s,t} n^p_{j,s,t} + w^w_{s,t} n^w_{j,s,t} + r^k_{s,t} \tilde{k}_{j,s,t} \\ & + \frac{\kappa_{n,s}}{2} \left[\left(\frac{n^w_{j,s,t}}{n^w_{j,s,t-1}} - 1 \right)^2 + \left(\frac{n^b_{j,s,t}}{n^b_{j,s,t-1}} - 1 \right)^2 + \left(\frac{n^p_{j,s,t}}{n^p_{j,s,t-1}} - 1 \right)^2 \right] \frac{(1 + \wedge_{s,t}) p_{s,t}}{p_t} y_{s,t} \Big\}, \end{aligned} \tag{9}$$

subject to (8), where $\frac{\kappa_{n,s}}{2}\left(n^o_{j,s,t}/n^o_{j,s,t-1} - 1\right)^2$ are quadratic labor adjustment costs for occupation $o = w, p, b$, expressed in units of the final consumption good, where the sector-specific parameter $\kappa_{n,s} \geq 0$ measures the extent of labor adjustment costs in the respective sector. The firm takes factor prices as given. The term $\beta^t \lambda_t / \lambda_0$ denotes the stochastic discount factor for real payoffs, where λ_t is the marginal utility of real income of the representative household that owns the firm.

The firm faces a quadratic cost of price adjustment. It chooses its price $p_{j,s,t}$ to maximize the discounted stream of profits, expressed in units of the final consumption good,

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \left(\frac{p_{j,s,t}}{p_t} \cdot y_{j,s,t} - mc_{j,s,t} \cdot y_{j,s,t} - \frac{\psi}{2} \left(\frac{p_{j,s,t}}{p_{j,s,t-1}} - 1 \right)^2 \frac{(1 + \wedge_{s,t}) p_{s,t}}{p_t} y_{s,t} \right), \tag{10}$$

subject to the demand function for variety j, $y_{j,s,t} = (p_{j,s,t}/p_{s,t})^{-\epsilon} y_{s,t}$, where $y_{s,t}$ is aggregate demand for the good of sector s, $p_{j,s,t}/p_{s,t}$ is the relative price of variety j within the sector, and $p_{s,t} = \left(\int_0^1 p^{1-\epsilon}_{j,s,t} di\right)^{1/(1-\epsilon)}$ is the price index of sector s. $mc_{j,s,t}$ denotes real marginal costs. The final term in (10) represents the costs of price adjustment, where $\psi \geq 0$ measures the degree of nominal price rigidity. Firms' first-order conditions can be found in the Appendix.

Market clearing, monetary and fiscal policy. The fiscal authority finances transfers and an exogenous stream of government spending g_t by labor and capital taxes. The government consumption bundle comprises goods 1 and 2 in a similar way than that of households,

$$g_t = \left(\zeta_g^{\frac{1}{\mu}} \cdot (g_{1,t})^{\frac{\mu-1}{\mu}} + (1 - \zeta_g)^{\frac{1}{\mu}} \cdot (g_{2,t})^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}}, \tag{11}$$

where ζ_g determines the steady-state share of good 1 in total government spending while, for simplicity, the elasticity of substitution between the two goods, μ is the same as for households. The government budget constraint (in real terms) reads

$$\frac{p_{g,t}}{p_t} g_t + T_t + (1 + r_{t-1}) \frac{b_{t-1}}{\pi_t} = b_t + \tau_t^n \left(w_t^b n_t^b + w_t^p n_t^p + w_t^w n_t^w \right) + \tau_t^k \left(r_{1,t}^k \tilde{k}_{1,t} + r_{2,t}^k \tilde{k}_{2,t} \right) , \tag{12}$$

where $p_{g,t} = \left(\zeta_g \cdot [(1 + \wedge_{1,t}) p_{1,t}]^{1-\mu} + (1 - \zeta_g) \cdot [(1 + \wedge_{2,t}) p_{2,t}]^{1-\mu} \right)^{1/(1-\mu)}$ is the price index of government spending and g_t follows an exogenous stochastic process with mean g. For a given g_t, the government determines its purchases of goods 1 and 2 such as to minimize purchasing costs. Tax rates, τ_t^k and τ_t^n, follow exogenous stochastic processes with means τ^k and τ^n. Government spending and tax shocks are contemporaneously financed by adjustments in government debt. In order to guarantee the stability of government debt, transfers follow the rule $\log(T_t) = (1 - \rho_T) \log(T) + \rho_T \log(T_{t-1}) - \gamma_b \cdot (b_{t-1} - b)/y$, where the parameter γ_b is positive and sufficiently large.

Monetary policy is described by the augmented Taylor rule

$$\log((1 + r_t)/(1 + r)) = \delta_\pi \log(\pi_t/\pi) + \delta_y \log(y_t/y) + \delta_g \log(g_t/g) , \tag{13}$$

where the parameters $\delta_\pi > 1$ and $\delta_y \geq 0$ measure the responsiveness of the nominal interest rate to consumer price inflation and aggregate output, respectively, where aggregate output, y_t, is defined as $y_t = (p_{1,t}/p_t) y_{1,t} + (p_{2,t}/p_t) y_{2,t}$. Following Nakamura and Steinsson (2014), the nominal interest rate may also directly respond to government spending, with responsiveness measured by $\delta_g \leq 0$.

Goods market clearing requires aggregate production in sector s, $y_{s,t}$, to be equal to aggregate demand for the sector-s good which includes sector-specific resources needed for capital utilization, price adjustment, labor adjustment, and product and labor wedges:

$$y_{s,t} = (1 + \wedge_{s,t}) \left(c_{s,t} + i_{s,t} + g_{s,t} + e(u_{s,t}) k_{s,t-1} + \frac{\psi}{2} (\pi_{s,t} - 1)^2 y_{s,t} + \frac{\kappa_{n,s}}{2} \left[\left(\frac{n_{s,t}^b}{n_{s,t-1}^b} - 1 \right)^2 + \left(\frac{n_{s,t}^p}{n_{s,t-1}^p} - 1 \right)^2 + \left(\frac{n_{s,t}^w}{n_{s,t-1}^w} - 1 \right)^2 \right] y_{s,t} \right) + \frac{p_t}{p_{s,t}} \left(\wedge_t^p w_{s,t}^p n_{s,t}^p + \wedge_t^b w_{s,t}^b n_{s,t}^b + \wedge_t^p w_{s,t}^w n_{s,t}^w \right) , s = 1, 2 . \tag{14}$$

Data-consistent employment. As the goods-market clearing conditions (14) show, the model economy produces some goods which are then wasted due to the wedges on goods and labor markets ($\wedge_{s,t}$ for $= 1, 2$ and $\wedge_t^o$ for $o = p, b, w$). We define data-consistent employment measures which corrects for the production of goods used to "pay" for the inefficiencies modeled by the wedges. Specifically, data-consistent employment by sector, $l_{s,t}$ ($s = 1, 2$), by occupation, l_t^o ($o = p, b, w$), as well as data-consistent aggregate employment, l_t, are given by

$$l_{s,t} = \frac{1}{1 + \wedge_{s,t}} \left(n_{s,t}^p (1 - \wedge_t^p) + n_{s,t}^b (1 - \wedge_t^b) + n_{s,t}^w (1 - \wedge_t^w) \right) , \tag{15}$$

$$l_t^o = (1 - \wedge_t^o) \left(\frac{n_{1,t}^o}{1 + \wedge_{1,t}} + \frac{n_{2,t}^o}{1 + \wedge_{2,t}} \right) , \tag{16}$$

and

$$l_t = l_t^w + l_t^b + l_t^p = l_{1,t} + l_{2,t}. \tag{17}$$

2.2 Data, calibration, and the pandemic shock

The parametrization is a combination of using empirical estimates for the U.S. from the literature for some parameters and calibrating others. Before we describe the calibration in detail, we first describe the data on industry and occupation used to calibrate the model.

We use Kaplan, Moll, and Violante (2020)'s classification of NAICS industries as either part of the social sector or the distant sector. Table A.1 in the Appendix shows this sectoral classification. The 23 major occupations groups from the 2018 Standard Occupational Classification System are aggregated into the white-collar, blue-collar, and pink-collar occupation groups as shown in Table A.2 in the Appendix.

We use the 2018 BLS industry-occupation matrix to determine the size of our three-occupation groups as well as their distribution over our two sectors. As can be seen in Table 1, the social sector uses pink-collar labor relatively intensively, whereas the distant sector is blue-collar intensive. White-collar employment, by contrast, is almost equally distributed across the two industry groups. We calculate average wages by occupation using the May 2018 National Occupational Employment and Wage Estimates from the Occupational Employment Statistics. Workers in white-collar occupations earn the highest hourly wage rates (approximately \$33), followed by blue-collar workers with an average hourly wage rate of roughly \$23. Workers in pink-collar occupations earn the

Table 1: Share of aggregate employment in sector-occupation group cells.

	social sector	distant sector	$\sum$
white-collar occupations	23.4%	21.4%	44.7%
blue-collar occupations	6.0%	17.8%	23.8%
pink-collar occupations	26.3%	5.1%	31.4%
$\sum$	55.7%	44.3%	100%

Notes: Results aggregated from the 2018 BLS industry-occupation matrix.

least, having an average wage rate of about $16 per hour.

We calibrate the model such that sector 1 is the social sector, and sector 2 is the distant sector. One period is one quarter. The intertemporal elasticity of substitution in consumption, σ, is set to 1. We use the estimates in Schmitt-Grohé and Uribe (2012) to quantify the wealth elasticity $\chi = 0.0001$, the elasticity of capital utilization $\Delta = \delta_1/\delta_2 = 3$, and the investment adjustment costs $\kappa_i = 9$. We set the Frisch elasticity of labor supply, which equals the parameter η when χ is close to zero, to 0.72, taken from Bredemeier, Gravert, and Juessen (2019).

We use the U.S. estimate for the degree of labor mobility across sectors by Horvath (2000) and set $\omega = 1$. We set the elasticity of substitution between goods within a sector to $\epsilon = 6$ implying a steady-state markup of prices over marginal costs equal to 20%. The elasticity of substitution in consumption between the goods of both sectors is set to $\mu = 1$. For some goods, this value tends to overestimate the substitutability between social-sector products and the average distant-sector good. For example, it is difficult to think about consumers substituting health services for the typical distant-sector good. However, there are arguably also goods for which the degree of substitutability is far higher. For example, consumers can easily switch from buying products at bricks and mortar retailers (social sector) to online shopping (distant sector). We, therefore, choose the standard Cobb-Douglas case of $\mu = 1$ as our baseline value.

The quarterly capital depreciation rate, δ, and the discount factor, β, are set to $\delta = 0.022$ and $\beta = 0.9927$. These values imply an aggregate capital to output ratio of 3.6 and an annualized real interest rate of around 3 percent. We parameterize the cost of price adjustment, ψ, to generate a slope of the Phillips curve consistent with a probability of adjusting prices in the Calvo model equal to 1/3, as estimated by Smets and Wouters (2007). This delivers $\psi \approx 30$. The steady-state tax rates and the annualized steady-state debt to GDP ratio are set to $\tau^n = 0.28$, $\tau^k = 0.36$, and $b/(4y) = 0.63$, as calculated by Trabandt and Uhlig (2011). The responsiveness of government transfers to changes in government debt is set to $\gamma_{sb} = 0.04$ to ensure debt sustainability. The coefficients of the Taylor rule measuring the responsiveness of the interest rate to inflation and output are set to $\delta_\pi = 1.5$ and $\delta_y = 0.5/4$, as proposed by Taylor (1993). We impose a zero net inflation steady state ($\pi = 1$).

The steady-state share of government spending in total output is set to the standard value of 0.2. We set the autocorrelation of government spending to $\rho_g = 0.9$. To calibrate the parameter ζ_g, which determines the distribution of government spending across sectors, we use the information on government spending for education and health services, the major components of public spending in the social sector. According to data from the World Bank Database and Congressional Budget Office, expenditures of federal, state, and local governments amount to 5% of GDP for education and 6% of GDP for health services, net of tax preferences. Hence, we consider government expenditure in the social sector to be 11% of GDP. With a total share of government spending in GDP of 20%, this gives a share of social-sector government expenditures in total government expenditures of $\zeta_g = 0.55$.

The weights on labor in the utility function, Ω^p, Ω^b, and Ω^w, are chosen to generate a steady-state occupation mix of employment consistent with the empirical counterpart displayed in Table 1. We set the share parameters $\aleph^p$, $\aleph^b$, $\aleph^w$, υ_1, υ_2, α_1, α_2, γ_1, γ_2, and ζ to match the composition of occupations across industries displayed in Table 1 as well as the relative occupational wages rates along with a labor income share of 67%. We achieve these calibration targets by setting $\zeta = 0.5$, $\aleph^p = 0.84$, $\aleph^b = 0.25$, $\aleph^w = 0.52$, $\alpha_1 = 0.45$, $\alpha_2 = 0.9$, $\gamma_1 = 0.64$, $\gamma_2 = 0.51$, $\upsilon_1 = 0.5$, and $\upsilon_2 = 0.54$.

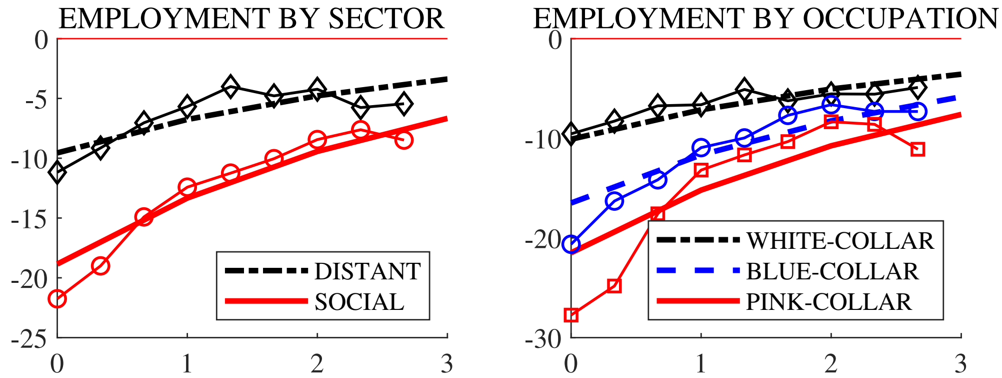
The following parameters are taken from Bredemeier, Juessen, and Winkler (2020), where we parameterize a multi-sector, multi-occupation New Keynesian business cycle model to match the estimated effects of U.S. government spending shocks. The parameter δ_g, which captures the responsiveness of the nominal interest rate to government spending, is $\delta_g = -0.364$. In Bredemeier, Juessen, and Winkler (2020), we use this value to match the estimated government spending multiplier. The parameters governing the size of labor adjustment costs in both sectors are $\kappa_{n,1} =$

1.03 and $\kappa_{n,2} = 3.33$. These values match the empirical evidence on the response of relative sectoral employment to government spending shocks, together with a weighted average of labor adjustment costs of 1.85, as estimated by Dib (2003). The elasticities of substitution with capital services are $\phi = 2.7$ for blue-collar work, $\theta = 0.07$ for pink-collar work, and $\iota = 1$ for white-collar work, respectively. In Bredemeier, Juessen, and Winkler (2020), we show that these values rationalize the relative occupational employment dynamics in response to U.S. government spending shocks. At the same time, they imply an average elasticity of substitution between capital services and labor of one, as in the canonical Cobb-Douglas case.

Pandemic shock. We expose the model economy to a pandemic shock, which we calibrate to match job losses during the Covid-19 crisis in 2020 and their distribution over sectors and occupation groups. The pandemic scenario we consider is not meant to explain the labor market outcomes in the Covid-19 crisis as we mostly use exogenous wedges to match empirical observations. The scope of our pandemic scenario is rather to set the scene for the policy analyses described in the next section, which we want to conduct in an environment mimicking the labor-market situation during the Covid-19 crisis as closely as possible. In particular, we want to analyze the ability of fiscal policy to create jobs where they were lost. While, in a model like ours, the isolated effects of a shock, e.g., a fiscal policy innovation, are barely affected by the state of the economy when the shock hits, it is worth mentioning that these isolated effects are not our primary focus. Instead, our aim is to study how well the distribution of jobs created by different fiscal policy impulses fits the needs following a pandemic, i.e., the distribution of job losses due to the pandemic shock.

We use data from the Current Population Survey (CPS) to measure sectoral and occupational employment dynamics in 2020. In April 2020, employment was about 17% below employment in February, which we use to describe the pre-pandemic reference situation. As discussed before, job losses were distributed unevenly across sectors and occupations. The lines with markers in Figure 3 show group-specific employment levels relative to February 2020, and the lines without markers are fitted log-linear regression lines. To be consistent with the subsequent model analysis, time is shown in quarters after the start of the pandemic. The left panel of the figure shows that employment in the social sector fell about twice as much as in the distant sector. The right panel shows the significant job losses in the pink-collar occupation group, where employment fell by

Figure 1: Sector-specific and occupation-specific employment, relative to pre-pandemic, CPS data, April through December 2020.



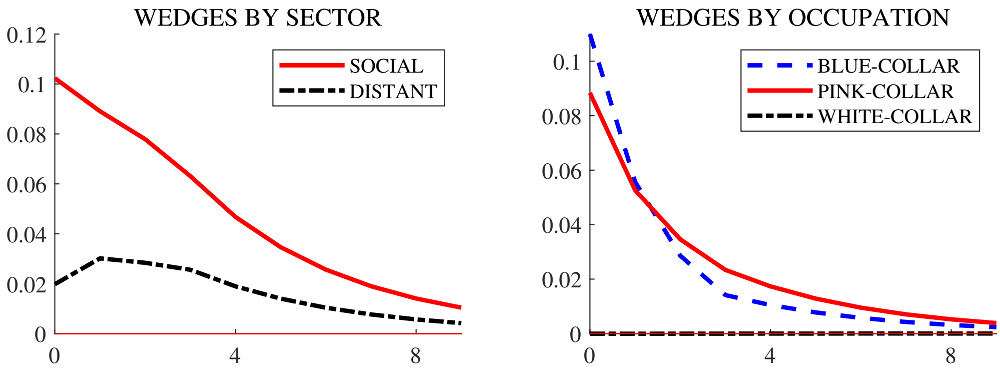
Notes: Calculated from CPS data. See Tables A.1 and A.2 for the classification of industries and occupations into the groups considered here. To account for seasonality in employment, time series calculated from the CPS were adjusted by the ratio of the seasonally adjusted series for total non-farm employment provided by the BLS and its non-adjusted counterpart. Horizontal axes show quarters after onset of pandemic.

almost 30%. In contrast, in the white-collar occupation group, it fell by only about 10%. Blue-collar workers were also hit hard by the Covid shock, with a drop of more than 20%. After April, employment in both sectors and all three occupation groups began to rise again and did so quite quickly at first. Employment growth flattened out over the year, and there was even a slight decline in December. However, this is widely seen as a temporary phenomenon related to the turbulent government transition and the slow start of vaccination.

For our analysis, the speed of group-specific recoveries is essential as it determines expected future developments that form the background of our policy analysis. The figure shows that, while the groups were affected very differently by the initial employment decline, they subsequently return toward their pre-pandemic levels at fairly similar paces. The hypothesis that the employment series exhibit the same persistence cannot be rejected statistically. The lines without markers in Figure 3 show estimated AR processes with common persistence, fitted to the empirical employment dynamics. We feed these smoothed trajectories into our model, which we then use to extrapolate employment dynamics.

Using the 2020 employment numbers for our pandemic scenario has the advantage that, in this year, no significant aggregate demand management through fiscal policy has taken place since the government's primary concerns were infection-fighting and disaster relief. Hence, using the 2020 numbers and projecting them into the future yields a reasonable scenario of how the economic crisis unfolds without substantial aggregate demand management. We use the entire path of

Figure 2: Distortions to product and labor markets (wedges) in the pandemic scenario.



Notes: Absolute values of the wedge processes $\wedge_t^s$ (left) and $\wedge_t^o$ (right). Horizontal axes show quarters after onset of pandemic.

group-specific employment in 2020 and do not give disproportionate weight to the slowdown of the recovery toward the end of the year. This implies that we may be looking at a rather optimistic scenario. We prefer to err on this side as it ensures we do not overstate the need for aggregate demand management.

In our model, we use the "wedges" to generate the empirically observed employment developments. In particular, we choose shocks to the wedges that allow the model to match exactly the smoothed employment paths by sector and occupation during the Covid shock in April 2020 and the subsequent three quarters (see lines without markers in Figure 3). From then on, we use our model to project the future path of the recovery. To discipline the projection, we assume that the wedges die out following an autoregressive process of order one and set the autocorrelation to 0.741 to match the projection by the Congressional Budget Office (CBO) that employment reaches its pre-pandemic level in May 2024.[8]

While it is not our primary concern to understand the Covid crisis in the labor market, it is nevertheless interesting to investigate the wedges required by the model to match the targets. Figure 2 shows the wedges. The vertical axis displays quarters after the economy was first hit by the pandemic shock ($t = 0$ corresponding to April 2020). To match the five group-specific employment levels per quarter, we need four wedges since both sectoral and occupational employment levels add up to total employment. We normalize the white-collar wedge to zero, as white-collar employment is the least affected by the crisis.

[8]Technically, we require the percentage deviation of employment from steady state to be less than 0.2% four years after the economy was first hit hard by the pandemic shock.

To replicate the labor-market dynamics in the Covid crisis, the model chooses a strong initial wedge in the social sector, which plausibly reflects social-distancing guidelines and other impediments to transactions that usually require substantial direct worker-client interactions. By contrast, the initial direct hit to the distant sector is not as hard and then increases somewhat when the crisis begins to spill over into this part of the economy. A few months into the pandemic, both sectoral wedges gradually decline. Occupational wedges (see right panel) spike at the outset of the pandemic, both for pink-collar and for blue-collar workers. These distortions can be understood as stay-at-home orders and other aspects of the crisis that make working difficult in occupations where working from home is not possible. These aspects of the pandemic hit pink-collar workers hard. Blue-collar labor markets are also exposed to substantial wedges as these workers concentrate in the distant sector and the model accordingly assigns large occupational wedges to them in order to match the pronounced fall in employment among this group during the pandemic, see Figure 3.

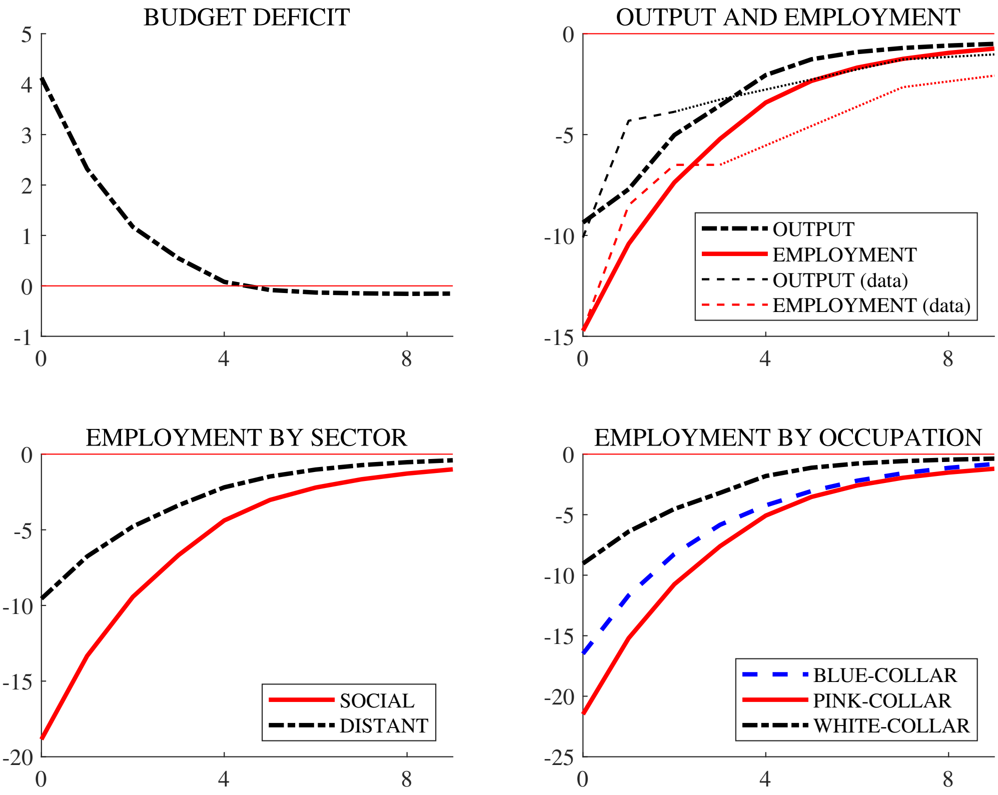
Subject to these wedges, the model produces profiles for the main variables depicted in Figure 3. We assume that the economy was at its steady state before the crisis. All variables are expressed in percentage deviations from their pre-crisis (steady-state) levels, except for the budget deficit, which we measure in percent of steady-state GDP.

The model predicts the budget deficit to rise by 4.1% percent of steady-state GDP in response to the crisis. In our model, this is a consequence of the collapse in tax revenues only as we do not model the budgetary costs of infection-fighting and disaster relief. Therefore, the actual budgetary costs of the Covid-19 crisis are likely higher. In April 2020, the CBO projected the deficit for the year 2020 to increase by 7.7 percent of 2019 GDP.[9]

The upper-right panel of Figure 3 shows the path of output and employment in our scenario. Aggregate employment falls by 15% on impact and then recovers gradually. The response of output, which is non-targeted in our scenario, is well in line with the data and the CBO projections. Our model predicts that output plummets by 9.4% when the pandemic hits the economy, which is only slightly less than the empirical drop of 10.1% in the second quarter of 2020. The recovery of output in the model is initially somewhat slower than what was observed during the first months of the

[9] We calculate this number as the projected increase in the deficit-to-GDP ratio minus the projected percentage decline in GDP. The May 2020 and February 2021 outlooks did not include deficit forecasts.

Figure 3: Baseline pandemic scenario



Notes: Deviations from steady state. Budget deficit in percent of steady-state GDP. All other variables in percent of their own steady-state values. Thin dashed lines ('data') show employment (red) in April 2020, July 2020, October 2020, and January 2021 relative to February 2020 and real GDP (black) in the second, third, and fourth quarter of 2020 relative to the fourth quarter of 2019. Thin dotted lines show employment (red) and GDP (black) projections of the CBO as of February 2021. GDP data and projections are adjusted for trend growth as projected by the CBO. Horizontal axes show quarters after onset of pandemic.

Covid-19 crisis, where it bounced back more quickly than employment. Later on, the dynamics in our model match CBO forecasts for the Covid-19 crisis – which predict a substantial slowdown in the output recovery – rather well. The CBO projects output to reach its potential not earlier than 2025 and thus after employment has recovered to its pre-pandemic level. In our pandemic scenario, employment overtakes production in their respective recoveries back to steady state after three years.

The lower panels of the figure show the responses of employment by occupation and sector. While the initial job losses by sector and occupation are targeted in our calibration of the pandemic shock, we do not target a sector-specific or occupation-specific speed of recovery from $t = 3$ onward. The model predicts employment in the distant sector to recover at a below-average pace as it is slowed by the stronger labor adjustment costs in this sector. Regarding occupations, the model predicts blue-collar employment recovers somewhat more slowly than pink-collar employment. This is due to the stronger labor adjustment costs that blue-collar workers face due to their concentration in the distant sector. As the pandemic fades away, firms rehire pink-collar workers more quickly than blue-collar workers, for whose employers hiring is more expensive.

3 Policy scenarios

In this section, we study the effects of aggregate demand management on the recovery from the pandemic shock as projected by our model. We consider three different, discretionary, government spending expansions that differ by the distribution of purchases across sectors and three tax cut scenarios that differ by the treatment of capital and labor income. As discussed in the introduction, we focus on aggregate demand management when the infection rate is under control and most restrictions on economic activity are relaxed. We choose $t = 4$ (one year after the onset of the pandemic, in the Covid crisis roughly the second quarter of 2021) as the starting point of aggregate demand management. Before that, we assume, following the mainstream view (expressed by, e.g., Oliver Blanchard), that there is no possibility to affect economic activity through aggregate demand management – including the announcements of future policy measures - since economic activity is restricted by the measures to contain infections (and, in our model, by the wedges mimicking these distortions to the economy). In particular, we do not believe that anticipation effects of future fiscal stimulus measures have significant effects on economic activity *in these first phases of the Covid crisis. Therefore, we model the policy measures as unanticipated, which constitutes the most straightforward way to shut off anticipation effects.* We quantify the size of the expansionary impulse to achieve a full recovery of aggregate employment in $t = 6$ (18 months after the beginning of the pandemic, roughly the end of 2021 in the Covid crisis). While this constitutes an ambitious goal, we want to compare policy measures that have the same effect on total employment, which allows us to concentrate on their differential effects on the employment composition.

3.1 Spending expansions

We first consider expansions in government spending. Our focus is on the disaggregated employment developments during the recovery. As discussed in Section 2, disaggregated employment dynamics in our model are driven by two channels, one that relates to differences in economic activity across sectors and their resulting composition effects and one that relates to capital-labor substitution within industries. In the recovery supported by spending expansions, these two channels work as follows.

The spending stimulus boosts aggregate demand, which leads to increased factor demand and, hence, tends to promote the recovery of employment. Mechanically, the more additional government purchases accrue in any given sector, the more strongly the recovery in this sector tends to be accelerated. Via *composition effects*, this can also help stimulate the employment recovery for those occupation groups strongly represented in this sector.

The increase in factor demand also promotes the recovery in factor prices. This is more pronounced for labor, which is in less elastic supply than capital services. Therefore, firms return production toward normal levels by predominantly raising their use of capital services, which remain cheap. This is achieved by raising capital utilization, which dominates the investment crowding-out of spending expansions. The more intensive use of capital lowers the marginal productivity of its close substitute, blue-collar labor, weakening the recovery of blue-collar work. On the contrary, the more intensive use of capital raises the marginal productivity of its close complement, pink-collar labor, reinforcing the recovery of pink-collar employment. The increase in white-collar employment, for which the elasticity of substitution with capital services is equal to unity, lies in between the increase of pink-collar and blue-collar labor employment. At the sectoral level, the *capital-labor substitution* channel, in isolation, implies that a spending expansion tends to promote the employment recovery relatively strongly in sectors that employ many pink-collar workers and more weakly in industries employing relatively many blue-collar workers. Put differently, the job multiplier is higher in pink-collar intensive sectors.

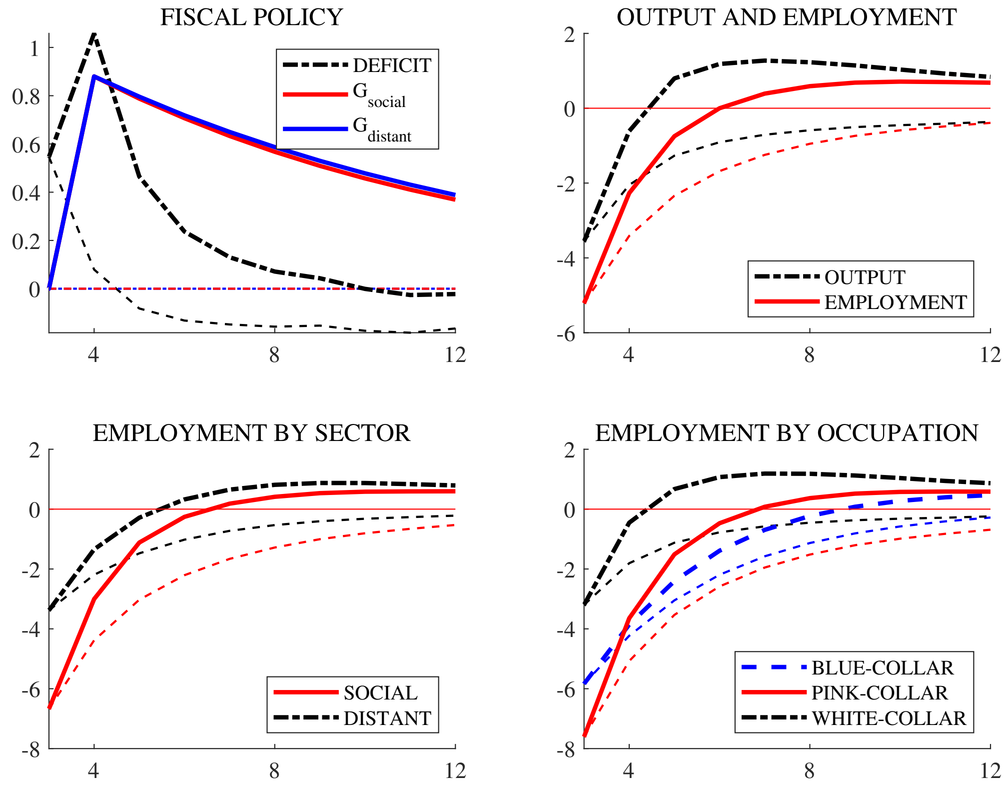
As we will discuss in detail below, the distribution of government spending across sectors shapes the recovery of employment by sector, but it does not affect considerably the strength and speed of the employment recovery by occupation. This indicates that composition effects due to sectors having a different occupation mix play only a limited role and that the capital-labor substitution channel is most important for the occupational employment effects of spending expansions.

Distributing additional purchases evenly across sectors. We start with a fiscal stimulus where the government increases its purchases in both sectors by the same amount. The upper-left panel of Figure 4 shows spending in both sectors as well as the primary fiscal deficit in percent of steady-state GDP. To increase readability, we concentrate on quarters 3 through 12 in what follows. Additional government purchases amount to 1.8% of quarterly steady-state GDP (corresponding to about \$100 billion using 2019 GDP numbers) one year after the pandemic started ($t = 4$). The stimulus is then slowly phased out with autocorrelation of 0.9. Over a four-year horizon, additional government spending amounts to 15% of quarterly steady-state GDP or about \$770 billion. The government attributes half of the spending boost to each of the two sectors, so 0.9% of a quarterly GDP initially or about 7.5% of a quarterly GDP (about \$335 billion) over four years. Recall that the size of the impulse is chosen to bring aggregate employment (displayed in the upper-right panel of Figure 4) back to its steady state ne and a half years after the pandemic hit the economy ($t = 6$). For the time thereafter, the model predicts a moderate boom in aggregate employment. The boost to aggregate demand accelerates the recovery of output. When the stimulus measure takes effect, it raises output by about 82 Cents per Dollar spent – a fiscal multiplier which is well in line within the range discussed in the empirical literature (see Ramey, 2016 for an overview). In the following, output returns to its pre-crisis level relatively quickly, overshoots, and gradually returns to the steady state thereafter.

The lower-left panel of Figure 4 shows that the employment composition by sector is stabilized relatively strongly by the spending boost. From the fifth quarter in our analysis onward, the lines in the figures are less than one percentage point away from each other. This indicates that remaining employment losses relative to steady state in both sectors are roughly proportional to steady-state sector size. This appears surprising at first, given the substantial pandemic job losses in the social sector and the symmetry of the fiscal package. The reason is that the job multiplier in the social sector, which employs relatively many pink-collar workers, is larger than in the distant sector, which employs relatively many blue-collar workers.

Although the sectoral composition of employment is almost back to normal rather quickly in this scenario, its occupational composition is destabilized for over three years, see the lower-right panel of Figure 4. For over three years, employment is biased toward white-collar occupations and away from blue-collar occupations. White-collar employment is back to steady state shortly after the fiscal stimulus kicks in and above steady state thereafter. By contrast, it takes over

Figure 4: Recovery from pandemic downturn with an equal spending expansion across sectors

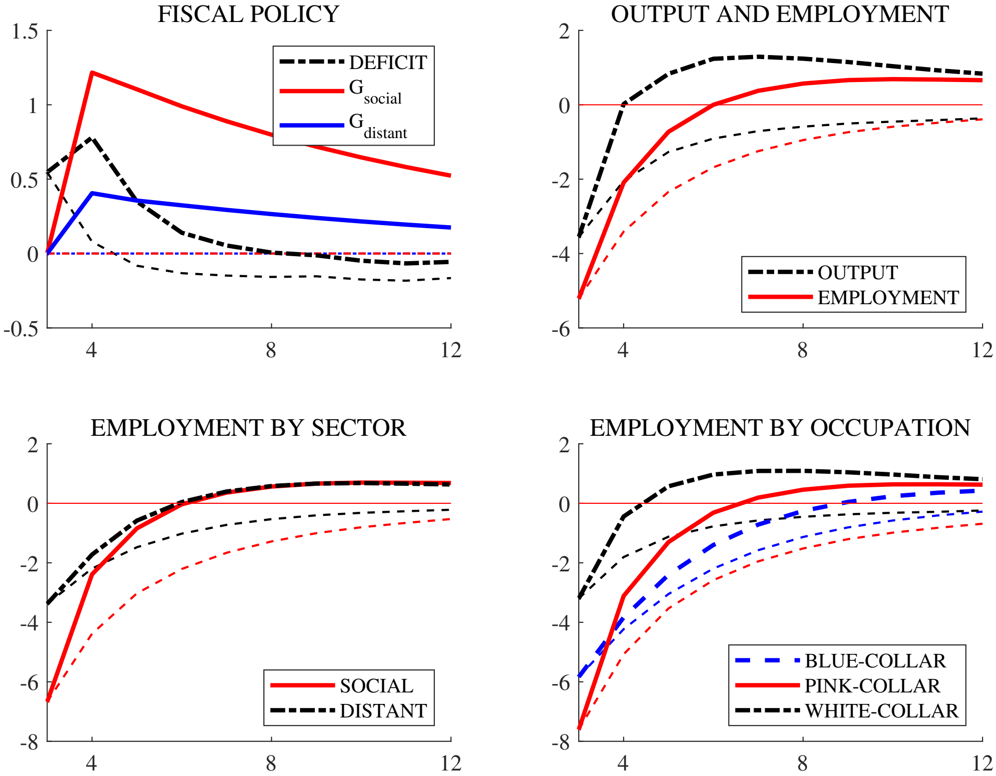


Notes: Deviations from steady state. Budget deficit and government spending by sector in percent of steady-state GDP. All other variables in percent of their own steady-state values. Dashed lines show pandemic scenario without fiscal policy intervention. Horizontal axes show quarters after onset of pandemic.

a year longer for blue-collar employment to recover to its pre-pandemic level (which happens in quarter 9). Pink-collar employment lies in between, with a return to steady state almost two years after the onset of the pandemic ($t = 7$) and a post-pandemic boom that is less pronounced but of similar duration as the one for white-collar employment. As explained before, the reason why blue-collar employment benefits the least from the demand stimulus lies in its relatively high degree of substitutability with capital services, weakening its recovery relative to other occupation groups.

Spending expansion biased toward social sector. We now investigate a scenario where three-quarters of the government's additional expenditures accrue in the social sector. Such a stimulus package can be thought of as primarily expanding public education or health expenditures. The total stimulus now amounts to roughly 1.6% of steady-state GDP or \$90 billion of which about \$65 billion is spent in the social sector, see the upper-left panel of Figure 5. The responses of aggregate employment and output, shown in the upper-right panel of Figure 5, are similar to the

Figure 5: Recovery from pandemic downturn with a spending expansion strongly directed into the social sector



Notes: Deviations from steady state. Budget deficit and government spending by sector in percent of steady-state GDP. All other variables in percent of their own steady-state values. Dashed lines show pandemic scenario without fiscal policy intervention. Horizontal axes show quarters after onset of pandemic.

scenario with an equal spending expansion across sectors as the sizes of the stimulus packages are chosen to achieve a full recovery of aggregate employment in quarter 6.

The lower-left panel shows the sector-specific employment recoveries. Not surprisingly, directing more spending toward the social sector induces this sector to recover more quickly. Social-sector employment, though hit harder by the pandemic shock, reaches its pre-crisis level 18 months after the pandemic struck and at the same time as employment in the less hard-hit distant sector. From that time onward, sectoral employment deviations from steady state are virtually identical, indicating that the sectoral composition of employment is the same as in steady state.

The quantitative effect on sector-specific employment is relatively small compared to the strong directing of government spending toward the social sector. It is dampened by reactions of private demand, which shifts toward the distant sector as goods and services produced in the social sector become relatively more expensive due to the surge in the government's demand for them.

As can be seen in the lower-right panel, the fiscal stimulus package directed mostly into the social sector accelerates the recovery of pink-collar employment in particular since pink-collar employment is represented disproportionately in the social sector. In quarter 4, when the fiscal stimulus comes into force, this spending expansion boosts the recovery of pink-collar work by about 0.5 percentage points more relative to the unbiased spending expansion (see Figure 4). Put differently, directing spending into the pink-collar intensive social sector reinforces the boost to pink-collar employment by roughly one third (two percentage points compared to one and a half).

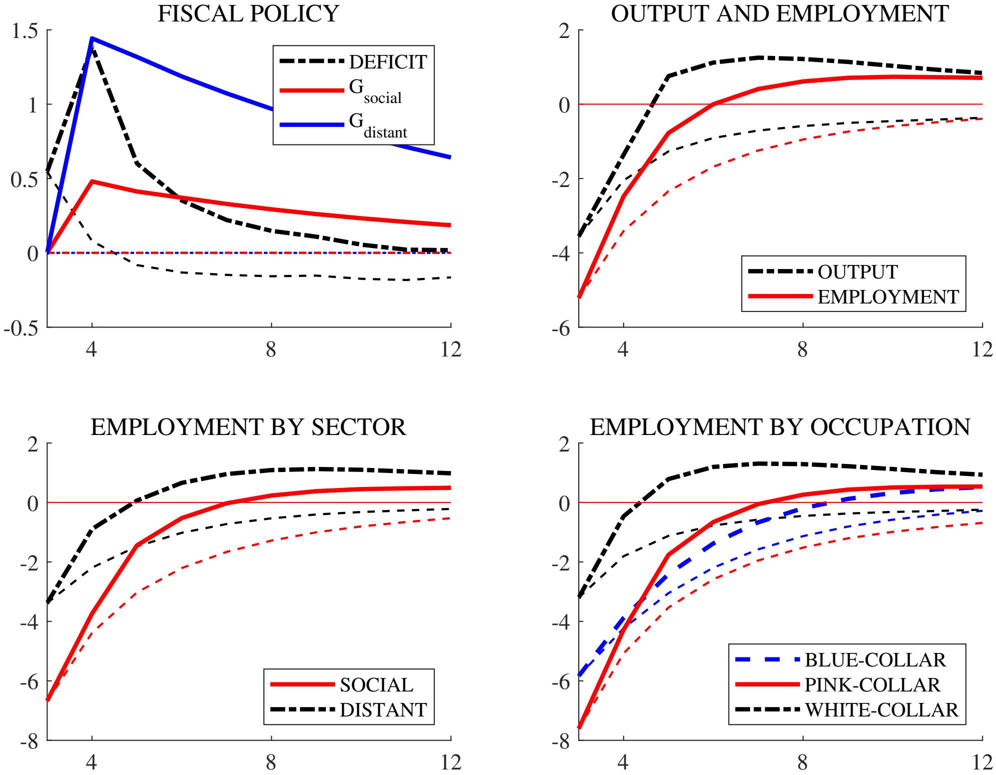
Blue-collar employment recovers somewhat more slowly in this scenario compared to the symmetric spending boost as it makes up only a small part of the workforce in the social sector where much of the direct effects of the stimulus takes effect. However, differences between the two scenarios with respect to the response of blue-collar employment are quantitatively small as the response to the biased spending expansion is less than a tenth weaker than the one to the unbiased spending expansion.

Overall, differences in occupation-specific employment dynamics to the unbiased spending expansion are relatively small compared to the strong biasing of the spending distribution across sectors. There are two reasons for this result. First, employment by sector does not respond too strongly to directing the stimulus to the hardest-hit sector since endogenous counteracting responses of private spending are strong. This is due to the combination of the change in the relative price of the sectoral goods and the substitution elasticity. Second, within-sector effects, driven by differences in capital-labor substitutability across occupations, are powerful and dominating the impact on employment by occupation.

Spending expansion biased toward distant sector. In this scenario, we analyze how far a spending expansion directed toward the distant sector can foster job creation for blue-collar workers. In particular, we consider a fiscal stimulus package in which three-quarters of the additional purchases accrue in the distant sector. Here, the total hike in government expenditures amounts to 1.9% of steady-state GDP (or about \$104 billion) in quarter 4. Of these expenditures, the government channels \$77 billion into the distant sector, see the upper-left panel of Figure 6. Again, the model-predicted acceleration of the aggregate recovery from the pandemic shock does not differ substantially from the other scenarios, see the upper-right panel of Figure 6.

As can be seen in the lower-left panel, employment in the distant sector recovers substantially

Figure 6: Recovery from pandemic downturn with a spending expansion strongly directed into the distant sector

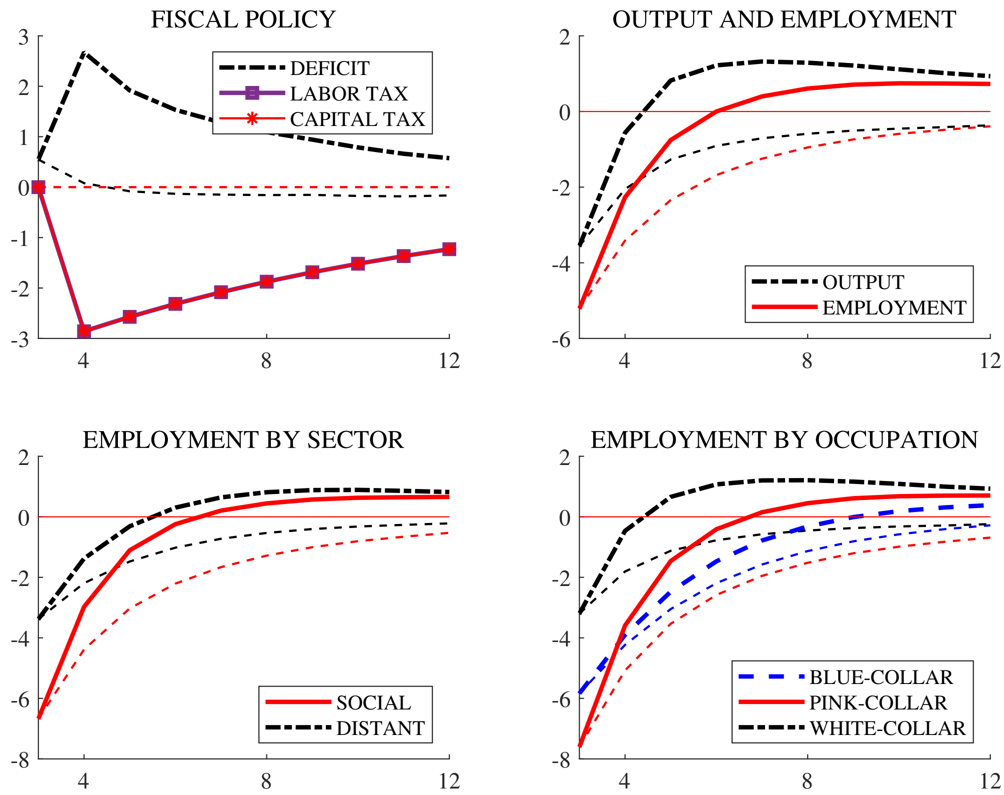


Notes: Deviations from steady state. Budget deficit and government spending by sector in percent of steady-state GDP. All other variables in percent of their own steady-state values. Dashed lines show pandemic scenario without fiscal policy intervention. Horizontal axes show quarters after onset of pandemic.

more quickly than employment in the social sector. This is due to the distant sector not being hit as hard by the pandemic shock and boosted disproportionately by fiscal stimulus. As a consequence of these two effects, the spending package directed mostly into the distant sector maintains destabilization of the economy's sectoral mix over the entire three years shown in the figure.

The sectoral destabilization may come at the benefit of a more substantial occupational stabilization, in particular an additional boost to the recovery of blue-collar employment. However, the lower-right panel of Figure 6 shows that the employment effects, by occupation, of directing the spending stimulus into the distant sector are small. Blue-collar employment recovers only slightly more strongly compared to the other packages. The responses of blue-collar employment differ barely across scenarios, amounting to only about 0.1 percentage points. Again, this can be explained by two countervailing influences. First, the biased spending expansion leads to an increase in the relative price of distant-sector goods, which induces households and firms to switch part of their expenditure to the social sector. Second, there are substantial changes in the occupation-mix

Figure 7: Recovery from pandemic downturn with a symmetric reduction in capital and labor income tax rates



Notes: Deviations from steady state. Budget deficit in percent of steady-state GDP. Tax rates in percentage points. All other variables in percent of their own steady-state values. Dashed lines show pandemic scenario without fiscal policy intervention. Horizontal axes show quarters after onset of pandemic.

within sectors favoring pink-collar and white-collar employment.

3.2 Tax cuts

We now turn to tax cuts as an alternative to expanding government purchases. First, we consider a scenario where the government cuts tax rates on both capital and labor income by the same absolute amount. We then turn to a scenario where only taxes on labor income are reduced and, finally, consider a cut only in taxes on capital income.

Cut in taxes on labor income and capital income. To start with, we consider a reduction in tax rates on both labor income and capital income by 2.85 percentage points in quarter 4 of our analysis, which achieves the target of a completed recovery of aggregate employment by quarter 6. When it takes effect, the tax cut leads to a surge in the primary fiscal deficit of about 2.6 percent of steady-state GDP, or about \$140 billion, see the upper-left panel of Figure 7.

The tax cut makes the use of production factors cheaper for firms, which hence return production toward pre-crisis levels. The upper-right panel of Figure 7 shows that this takes place relatively quickly, and that output has fully recovered one quarter after the tax stimulus. This and the subsequent post-pandemic boom are similar to the spending expansions considered before. The duration of the employment recovery is, by construction, precisely the same across scenarios and reflects the target of a full aggregate employment recovery half a year after the stimulus. The relation between output and employment is not affected substantially by whether the fiscal stimulus is executed via a spending expansion or a symmetric tax cut.

Turning to the disaggregated effects of the stimulus, the mechanisms are similar to those at play in response to the spending expansions. As firms are incentivized to take back some of the reduction of factor demand, the recovery of factor prices is accelerated. As in the spending scenarios, this effect is more pronounced for labor, which is less elastically supplied than are capital services. As a consequence, firms act more quickly in bringing back their use of capital services toward pre-crisis levels while they are more reluctant toward calling back workers. The tax cut boosts both capital utilization and investment, with the former being the dominant force. This substitution toward capital services slows down most strongly the recovery of employment in blue-collar occupations where capital-labor substitution is easiest. Again, this also impacts on sectoral employment as relatively little jobs are created by the stimulus in industries with many blue-collar workers and hence a high average degree of capital-labor substitutability.

Hence, the employment effects of the tax stimulus are more substantial in the social sector, and the tax cuts predominantly help this sector accelerate its recovery. The lower-left panel of Figure 7 shows that the social sector catches up to the distant sector around 15 months after the beginning of the pandemic, and both sectors experience somewhat parallel smooth upturns afterward. These developments are similar to those in the unbiased spending scenario considered in Figure 4.

The occupational employment dynamics displayed in the lower-right panel of Figure 7 also resemble those from the spending expansions. The tax stimulus accelerates the pink-collar recovery but pink-collar employment remains persistently below white-collar employment in terms of deviation from steady state. Blue-collar employment reaches its pre-crisis level as late as four years after the pandemic shock and workers in these occupations do not enjoy a post-pandemic boom.

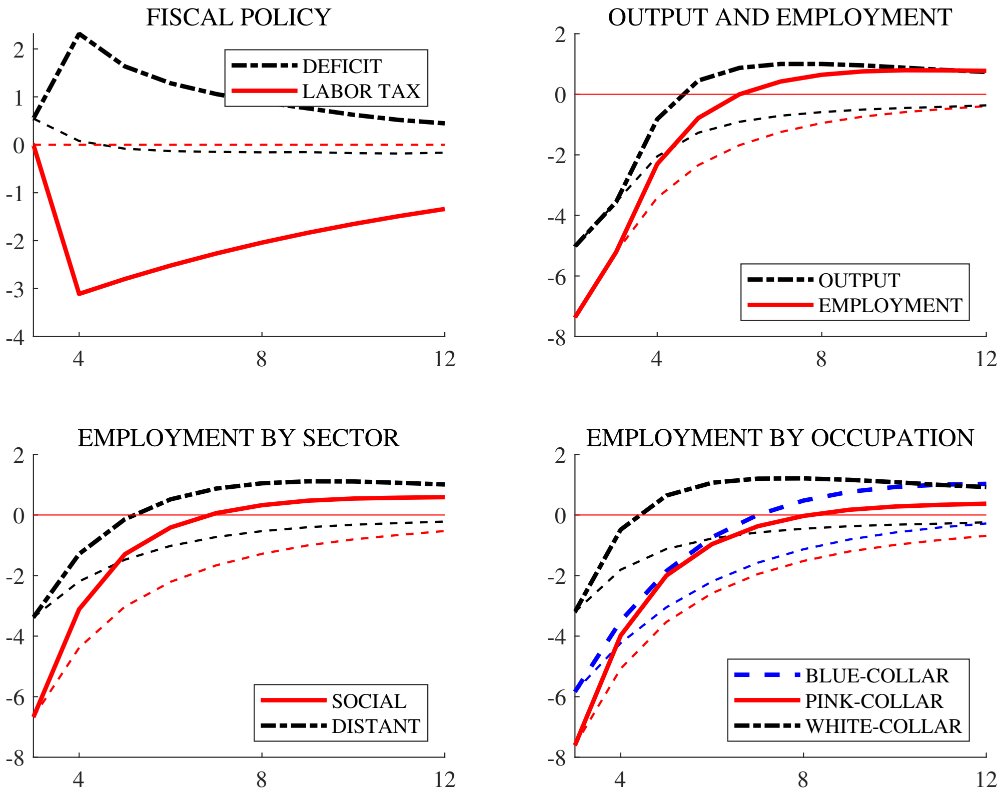
Labor income tax cut. Here, we consider a scenario where tax rates on labor income are cut but not those on capital income. This is an interesting scenario because the policy stimulus directly affects relative factor prices, which play an essential role in the transmission from fiscal policy to disaggregated employment dynamics. The tax rate on labor income has to be cut by about 3.1 percentage points to achieve the stabilization of aggregate employment. This tax cut would let the deficit surge by approximately 2.2% of a quarterly steady-state GDP, about $120 billion, see the upper-left panel of Figure 8. The aggregate employment effects are again similar to the ones in the other scenarios, which is a consequence of targeting the speed of the employment recovery. As the upper-right panel of Figure 8 shows, the recovery of output is less strongly accelerated than in the other scenarios as the stimulus only makes labor but not capital services less expensive for firms.

The disaggregated effects of the labor income tax cut differ from those of the stimulus measures in the previous scenarios. Cutting taxes on labor but not on capital alters the relative price of the two factors directly. With labor becoming relatively cheaper, firms return production to normal levels mostly by hiring more workers, whereas the use of capital services is raised only modestly. This shift in the composition of factors away from capital services and toward labor tends to increase the marginal product of blue-collar work, which is a close substitute for capital services. In contrast, it tends to decrease the marginal product of pink-collar work, which is a complement to capital services. This counteracts the tendency for strong employment effects in pink-collar occupations and in industries that employ many pink-collar workers. Firms' demand for blue-collar labor recovers more strongly than under the other stimulus programs. Through composition effects, this also leads to an accelerated recovery in the distant sector where relatively many blue-collar workers are employed. At the same time, it slows down the recovery in the social sector, compared to the stimulus measures discussed before.

As a consequence, the sectoral composition of the economy is not as strongly stabilized as it is by the symmetric tax cut or the unbiased spending boost. The lower-left panel of Figure 8 shows that the social sector lags more strongly behind the distant sector in terms of employment than in the other scenarios.

As seen in the lower-right panel of Figure 8, the labor income tax stimulus promotes job growth in blue-collar occupations considerably. Thus, blue-collar workers are not left behind during the

Figure 8: Recovery from pandemic downturn with a reduction in the labor income tax rate

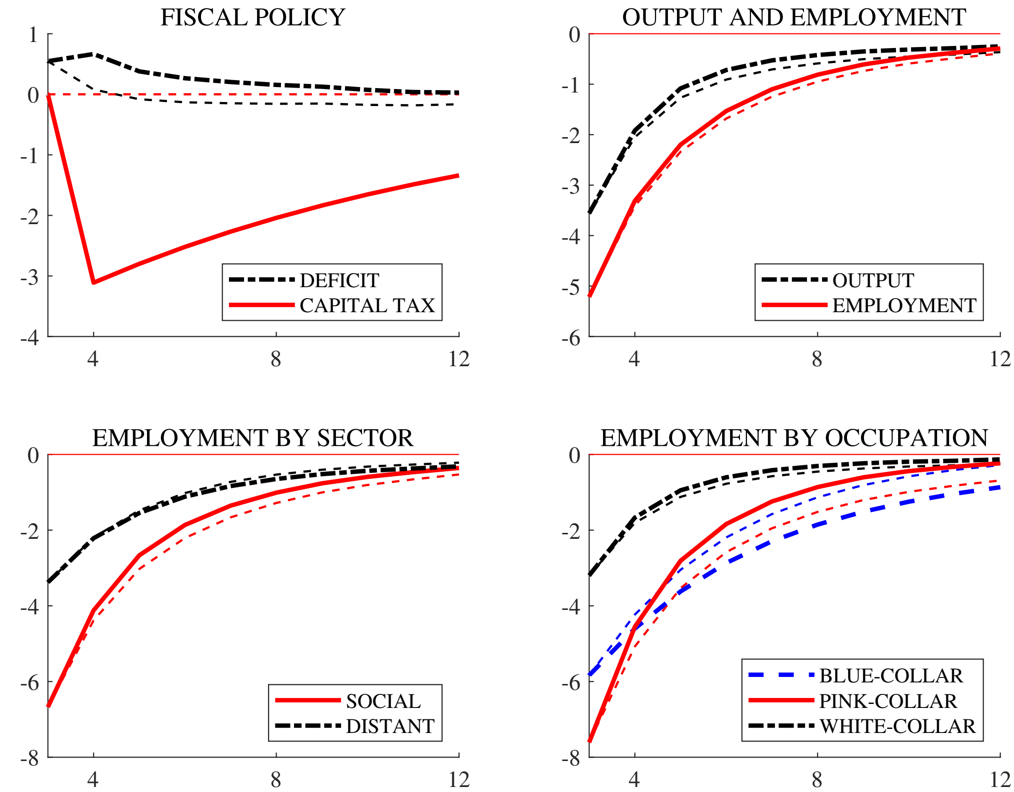


Notes: Deviations from steady state. Budget deficit in percent of steady-state GDP. Tax rates in percentage points. All other variables in percent of their own steady-state values. Dashed lines show pandemic scenario without fiscal policy intervention. Horizontal axes show quarters after onset of pandemic.

recovery under this policy scenario. Blue-collar employment recovers far more quickly than in any other scenario, achieving a full recovery to its pre-crisis level as early as quarter 7 of our analysis and thus half a year earlier than in the policy scenarios considered before and two and half years earlier than without any stimulus. In comparison, this policy measure achieves the most pronounced stabilization of the occupation mix of employment in the sense that devations from steady state are most similar across occupations.

Capital income tax cut. Finally, we consider a scenario where only tax rates on capital income are cut but not those on labor income. This policy change only affects a small part of aggregate income and, hence, any given absolute change in the capital tax rate affects economic activity less strongly than the same change in, e.g., the labor income tax. In particular, the effects on employment are small since employment is affected only indirectly. For this reason, we refrain from the stabilization target for aggregate employment as an immense cut of capital income tax rates would be needed to achieve it. Instead, we consider a reduction in tax rates on capital

Figure 9: Recovery from pandemic downturn with a reduction in the capital income tax rate



Notes: Deviations from steady state. Budget deficit in percent of steady-state GDP. Tax rates in percentage points. All other variables in percent of their own steady-state values. Dashed lines show pandemic scenario without fiscal policy intervention. Horizontal axes show quarters after onset of pandemic.

income by the same amount as tax rates on labor income are reduced in the previous scenario. In particular, tax rates on capital are reduced by 3.1 percentage points which leads to a deficit surge of about 0.6% of pre-crisis GDP (or about $30 billion), see upper-left panel of Figure 9.

This stimulus accelerates the aggregate recovery only slightly, see the upper-right panel of Figure 9. Given the relatively small stimulus considered in this scenario, this is not surprising. As a consequence of the change in relative factor prices, the capital-tax stimulus fosters the output recovery more strongly than the employment recovery.

At the disaggregated level, effects are the opposite of those of the labor-tax stimulus considered before. When the government directly reduces the costs of using capital services, the tendency of stimulus measures to promote job growth for pink-collar workers and leave out blue-collar workers are reinforced. Regarding sectors, this translates into a strong bias of the created jobs toward the social sector. Quantitatively, our results show that the recoveries of employment in the distant sector (lower-left panel of Figure 9) and blue-collar occupations (lower-right panel of Figure 9) are

Table 2: Distribution of cumulated employment effects of fiscal policy measures.

	spending expansions								
	$\Delta G_1 = \Delta G_2$			$\Delta G_1 > \Delta G_2$			$\Delta G_1 < \Delta G_2$		
	social sector	pink-collar	blue-collar	social sector	pink-collar	blue-collar	social sector	pink-collar	blue-collar
impact	0.67	0.39	0.08	0.84	0.47	0.07	0.38	0.27	0.09
one year	0.65	0.39	0.11	0.75	0.43	0.10	0.53	0.34	0.11
four years	0.61	0.38	0.14	0.68	0.41	0.14	0.52	0.35	0.15
	tax cuts								
	$\Delta\tau^n = \Delta\tau^k$			$\Delta\tau^n < 0$			$\Delta\tau^k < 0$		
	social sector	pink-collar	blue-collar	social sector	pink-collar	blue-collar	social sector	pink-collar	blue-collar
impact	0.69	0.41	0.07	0.64	0.31	0.16	1.06	1.19	-0.64
one year	0.66	0.41	0.10	0.60	0.30	0.20	1.23	1.46	-0.96
four years	0.62	0.40	0.12	0.56	0.29	0.24	1.48	2.00	-1.69

Notes: Table shows sector-specific and occupation-specific shares in the cumulated employment difference between pandemic scenarios with and without fiscal intervention. First column shows horizon with "impact" referring to the quarter where the fiscal intervention begins ($t = 4$) and "one year" and "four year" referring to the time span from the start of the intervention, i.e., $t = 4$ through $t = 8$ and $t = 4$ through $t = 20$, respectively.

even slowed down by the stimulus. The latter is especially remarkable due to blue-collar workers' substantial exposure to crisis-related job losses.

3.3 Taking stock

We now condense the main results of the policy analysis in comprehensive statistics that facilitate comparisons across stimulus measures. Table A.3 in the Appendix summarizes how the increase in employment due to the various fiscal stimulus measures is distributed across sectors and occupations. For example, the first column in each block of the table displays, over different horizons, the share of additional job-years created by fiscal policy that accrue in the social sector. The additional job-years are measured by the areas in the figures discussed before that lie between the employment paths with and without fiscal interventions up to a specific horizon. The distant sector and the white-collar occupation group, which suffered relatively little from the pandemic shock, are omitted from the table.[10]

Table A.3 shows that the symmetric spending expansion, the one targeted toward the social sector, and all three tax cuts are successful in directing a substantial share of the created jobs into

[10]Their share in the fiscally induced jobs is one minus the share of the social sector and, respectively, one minus the combined share of the pink-collar and blue-collar occupation groups.

Table 3: Cumulated job multipliers: job-years per $100K increase in deficit.

	spending expansions			tax cuts		
	$\Delta G_1 = \Delta G_2$	$\Delta G_1 > \Delta G_2$	$\Delta G_1 < \Delta G_2$	$\Delta\tau^n = \Delta\tau^k$	$\Delta\tau^n < 0$	$\Delta\tau^k < 0$
impact	0.82	1.32	0.50	0.31	0.35	0.17
one year	1.96	2.73	1.44	0.55	0.64	0.23
four years	3.23	4.22	2.54	0.82	1.00	0.22

Notes: Table shows cumulated employment difference between pandemic scenarios with and without fiscal intervention divided by the cumulated difference in the primary deficit between scenarios. First column shows horizon with "impact" referring to the quarter where the fiscal intervention begins ($t = 4$) and "one year" and "four year" referring to the time span from the start of the intervention, i.e., $t = 4$ through $t = 8$ and $t = 4$ through $t = 20$, respectively. Model units transformed to jobs and dollars by interpreting steady state GDP as 5.4 trillion (2019 quarterly average) and steady state employment as 151 million (2019 average).

the disproportionately suffering social sector. Regarding occupations, the table illustrates that pink-collar workers obtain a considerable share of the jobs created by all the policy measures. By contrast, blue-collar workers do not benefit strongly from most fiscal stimulus measures. In all spending expansions, their share in the created jobs is substantially below their share in pandemic-induced employment losses. The same is true for the symmetric tax cut and, as discussed before, blue-collar workers employment prospects even deteriorate when there is a cut in capital income taxes. The reduction in labor income tax rates promotes blue-collar employment most strongly.

To provide a complete picture of the policy measures, we now briefly discuss their cost-effectiveness. To this end, we calculate cumulated employment multipliers, which measure the cumulative change in employment relative to the cumulative change in the budget deficit (expressed in dollars) from the time of the fiscal innovation to a reported horizon (impact, one year, and four years in our case).[11] We express multipliers in terms of jobs per increase in the deficit to be able to compare spending hikes and tax cuts.

Table 3 shows that the symmetric spending expansion generates between one and three job-years per $100,000 increase in public debt, depending on the horizon. To put this into perspective, Chodorow-Reich (2019) finds that the fiscal stimulus during the Great Recession increased employment by about two job-years per $100,000 over a two-year horizon. Comparing the different spending packages in our model, we observe that they create more jobs per dollar when spending is more strongly directed toward the social sector, where the job multiplier is larger due to the

[11] Graphically, these multipliers are the area between employment paths and deficit paths with and without fiscal interventions, multiplied by the steady-state employment to GDP ratio to translate percentages into job-years per dollar spent.

more pronounced complementarity of the average worker's tasks to capital services. Tax cuts are, per dollar, less effective in raising employment, and this especially holds for reductions in capital income taxes, which create less than half the number of jobs per dollar compared to cuts in labor income taxes.

3.4 Effects on the income distribution

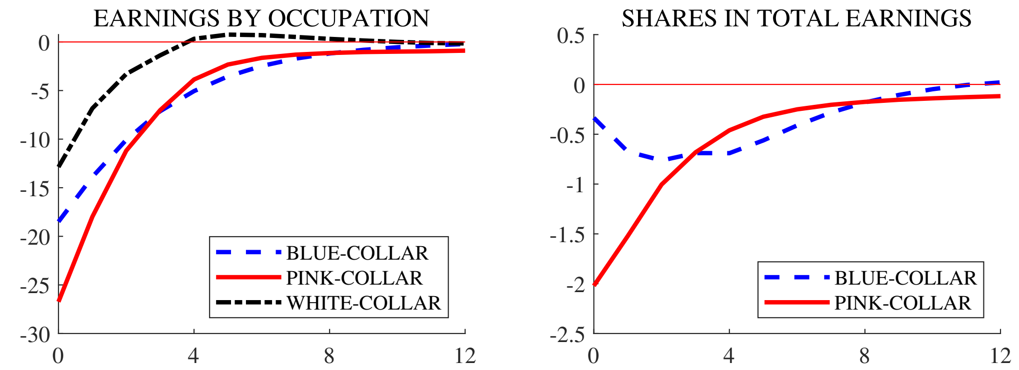
Pandemic job losses are concentrated in pink-collar and blue-collar occupations and hence in low-to-medium wage occupations. Not only employment but also labor income falls disproportionately in these groups, see the left panel of Figure 10(a). In contrast, white-collar workers, who usually earn more, experience smaller earnings losses. Consequently, income shares of low-income occupation groups decline during the pandemic, see the right panel of Figure 10(a). This leads to an increase in inequality and thus contributes to the social costs of the pandemic. This, in turn, implies that fiscal policy can reduce the costs of the pandemic if it succeeds in dampening the rise in inequality or accelerating its reduction during the recovery phase. We therefore now look at the distributional effects of the various policy measures. We are particularly interested in how the policy measures affect the income shares of pink-collar and blue-collar workers, respectively.

We first investigate the case when the government increases spending symmetrically across sectors. This stimulus mostly accelerates the recovery of white-collar and pink-collar workers' earnings, see the left panel of Figure 10(b). The right panel shows that the spending expansion fosters the pink-collar income share, which reduces inequality since pink-collar workers tend to earn the lowest wages. By contrast, relative blue-collar incomes further deteriorate because of this stimulus. First, blue-collar workers suffer disproportionately from pandemic job losses, and second, they are left out of jobs created by fiscal policy - hence their relative position is weakened twofold.

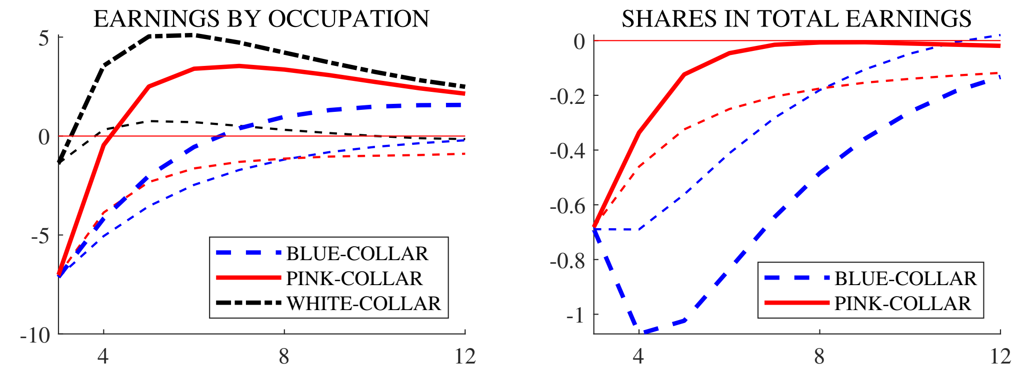
Figure 10(c) shows the reaction of the blue-collar income share in total earnings to determine which stimulus measures do promote relative blue-collar incomes. Most stimulus measures reinforce the deterioration of blue-collar workers' position in the income distribution. The cut in labor income taxes stands out. Initially, this measure only moderately reduces the income share of blue-collar workers and even strengthens their medium-term position.

Figure 10: Distributional consequences of the pandemic and the fiscal policy measures.

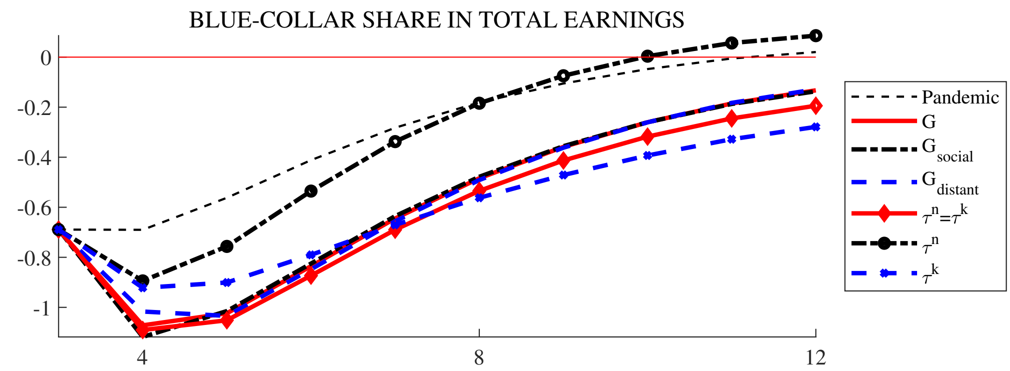
(a) Distributional consequences of the pandemic.



(b) Distributional consequences of symmetric spending expansion.



(c) Blue-collar share in total labor income for different fiscal measures.



Notes: Deviations from steady state. Earnings in percent of their own steady-state values. Earnings shares are in percentage points. Horizontal axes show quarters after onset of pandemic.

3.5 Sensitivity analysis

This section demonstrates how the main results of our quantitative analysis depend on modeling choices and parameter values. First, we impose constant capital utilization by setting the supply elasticity of capital services to zero. Second, we omit the direct feedback on government spending in the Taylor rule. Third, we remove sectoral differences in labor adjustment costs and use the average value for both sectors instead. Fourth, we include a wealth effect on labor supply, using the other limiting case, $\chi = 1$, in the utility function. Finally, we reduce the degree of price rigidity and choose the adjustment parameter equivalent to adjusting prices twice a year. Table A.3 in the Appendix shows the distribution of additional jobs created by fiscal policy for these recalibrations of the model.

Counterfactually imposing a constant degree of capital utilization changes our main results qualitatively. Under this assumption, it would be blue-collar workers who benefit particularly strongly from the stabilization efforts. This finding illustrates that the key mechanism behind our main results runs through an adjustment of the intensity with which the existing capital stock is used, as discussed before. In Bredemeier, Juessen, and Winkler (2020), we provide empirical evidence that firms increase the intensity of capital utilization in response to fiscal stimulus measures.

The other recalibrations leave our main conclusions regarding the distribution of fiscally created jobs unaffected (while they do affect the aggregate effects, the shape of responses, and the strength of distributional effects). For instance, the social sector benefits disproportionately from symmetric spending increases and tax cuts in all calibrations. In most calibrations, pink-collar workers benefit disproportionately from spending expansions and tax cuts, while blue-collar workers are mostly left out from these policies' labor-market benefits.

In our baseline calibration, the Taylor rule implies that the central bank amplifies the distributional effects of government spending through its endogenous response. Monetary accommodation keeps the real rate low in response to spending expansion, which incentivizes firms to use more capital services to the detriment of blue-collar employment. Thus, omitting the spending feedback of monetary policy (by setting $\delta_g = 0$) tends to allow for an accelerated recovery of blue-collar employment. However, as can be seen in Table A.3 in the Appendix, this effect is small, as the share of jobs going to blue-collar workers under a standard Taylor rule without monetary accommodation is similar to the baseline scenario with monetary accommodation. The results of this sensitivity check show that the capital-labor substitution channel is the dominant driver of differences in the employment effects of fiscal policy by occupation.

When we abstract from sectoral differences in labor adjustment costs, the share of jobs created in the social sector is somewhat reduced, but only in the very short run. Allowing for a wealth effect on labor supply tends to strengthen the distributional results, but the effects are small. While *some* nominal rigidity is essential for our model, variations in the degree of price stickiness hardly affect the distribution of jobs created but only affect the total number of jobs created per dollar spent.

4 Conclusion

The massive job losses in the Covid-19 crisis were disproportionately borne by workers in retail trade, hospitality, and other contact-intensive industries as well as by workers in blue-collar, sales, and service occupations. Given the high costs of switching industry or occupation, the total economic cost of a pandemic can be reduced if policy achieves stabilization not only of aggregate employment but also of the composition of employment, i.e., manages to foster rapid job growth in particular in those industries and occupations that were hit hardest by the crisis.

In this paper, we analyze the ability of different fiscal stimulus measures to achieve this goal. To do so, we use a multi-sector, multi-occupation dynamic stochastic general equilibrium model to study the effects of different types of fiscal policy instruments on employment by occupation and industry. In the model, heterogeneity in employment responses to a fiscal stimulus results from two channels. First, government spending can be distributed unevenly across sectors leading to disproportionate job growth in industries where purchases are increased considerably and affecting occupational employment through composition effects. Second, differences in the substitutability with capital services across occupations induce fiscal policy to create job growth predominantly in those occupations where labor is a complement to capital services.

Our model predicts that the two groups of occupations hit hard by the pandemic recession, pink-collar and blue-collar workers, profit differentially from a fiscal stimulus. All types of fiscal stimulus promote job growth in pink-collar occupations considerably. In this sense, fiscal policy is successful in helping create jobs where they were lost during the Covid-19 crisis – labeled as a “pink-collar recession” by some commentators. But this recession has, as previous ones, also struck blue-collar workers hard. To create jobs for this group of workers, a fiscal stimulus has to be designed in specific ways to circumvent or at least weaken the mechanisms that dampen the employment gains for blue-collar workers. Only a cut in labor income taxes generates a substantial number of blue-collar jobs and avoids an accelerated reduction in the share of income that goes to blue-collar workers.

The white-collar occupation group, which is relatively mildly affected by the Covid-19 crisis, enjoys some employment growth in all stimulus scenarios. Independent of how the fiscal stimulus is set up in detail, the recovery of white-collar employment is accelerated considerably. This implies that fiscal policy during the economic recovery from the pandemic shock also helps create jobs where not so many were lost in the first place.

Regarding sectoral employment, the weak capital-labor substitutability in the social sector, i.e., in industries with intensive face-to-face contacts between workers and customers, brings about pronounced job growth induced by fiscal stimulus measures in this sector. In our model analysis, this mechanism leads to a relatively quick stabilization of the economys industry mix even when a fiscal policy does not target the social sector explicitly.

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Appendix

Equilibrium conditions

This appendix collects the equilibrium conditions of our model. In a symmetric equilibrium, $y_{s,t} = y_{j,s,t}$, $\widetilde{k}_{j,s,t} = \widetilde{k}_{s,t}$, $n^p_{j,s,t} = n^p_{s,t}$, $n^b_{j,s,t} = n^b_{s,t}$, $n^w_{j,s,t} = n^w_{s,t}$, $mc_{j,s,t} = mc_{s,t}$, and $p_{j,s,t} = p_{s,t}$. Let $\pi_{s,t} = p_{s,t}/p_{s,t-1}$ denote gross price growth in sector s. The first-order conditions of firms in sector $s = 1, 2$ are then given by

$$y_{s,t} = y_{j,s} \cdot \left(\upsilon_s \cdot \left(\frac{v^p_{j,s,t}}{v^p_{j,s}} \right)^{\frac{\iota-1}{\iota}} + (1-\upsilon_s) \cdot \left(\frac{n^w_{j,s,t}}{n^w_{j,s}} \right)^{\frac{\iota-1}{\iota}} \right)^{\frac{\iota}{\iota-1}} \tag{A.1}$$

$$v^p_{j,s,t} = v^p_{j,s} \cdot \left(\alpha_s \cdot \left(\frac{v^b_{j,s,t}}{v^b_{j,s}} \right)^{\frac{\theta-1}{\theta}} + (1-\alpha_s) \cdot \left(\frac{n^p_{j,s,t}}{n^p_{j,s}} \right)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}} \tag{A.2}$$

$$v^b_{j,s,t} = v^b_{j,s} \cdot \left(\gamma_s \cdot \left(\frac{\tilde{k}_{j,s,t}}{\tilde{k}_{j,s}} \right)^{\frac{\phi-1}{\phi}} + (1-\gamma_s) \cdot \left(\frac{n^b_{j,s,t}}{n^b_{j,s}} \right)^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}} \tag{A.3}$$

$$mc_{s,t} \cdot mpk_{s,t} = r^k_{s,t} \tag{A.4}$$

$$\begin{aligned} mc_{s,t} \cdot mpl^b_{s,t} = {} & w^b_{s,t} + \kappa_{n,s} \left(\frac{n^b_{s,t}}{n^b_{s,t-1}} - 1 \right) \frac{(1+\wedge_{s,t})p_{s,t}}{p_t} \frac{y_{s,t}}{n^b_{s,t-1}} \\ & - \kappa_{n,s} \beta \, \mathrm{E}_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \left(\frac{n^b_{s,t+1}}{n^b_{s,t}} - 1 \right) \frac{(1+\wedge_{s,t+1})p_{s,t+1}}{p_{t+1}} y_{s,t+1} \left(\frac{n^b_{s,t+1}}{(n^b_{s,t})^2} \right) \right\} \end{aligned} \tag{A.5}$$

$$\begin{aligned} mc_{s,t} \cdot mpl^p_{s,t} = {} & w^p_t + \kappa_{n,s} \left(\frac{n^p_{s,t}}{n^p_{s,t-1}} - 1 \right) \frac{(1+\wedge_{s,t})p_{s,t}}{p_t} \frac{y_{s,t}}{n^p_{s,t-1}} \\ & - \kappa_{n,s} \beta \, \mathrm{E}_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \left(\frac{n^p_{s,t+1}}{n^p_{s,t}} - 1 \right) \frac{(1+\wedge_{s,t+1})p_{s,t+1}}{p_{t+1}} y_{s,t+1} \left(\frac{n^p_{s,t+1}}{(n^p_{s,t})^2} \right) \right\} \end{aligned} \tag{A.6}$$

$$\begin{aligned} mc_{s,t} \cdot mpl^w_{s,t} = {} & w^w_t + \kappa_{n,s} \left(\frac{n^w_{s,t}}{n^w_{s,t-1}} - 1 \right) \frac{(1+\wedge_{s,t})p_{s,t}}{p_t} \frac{y_{s,t}}{n^w_{s,t-1}} \\ & - \kappa_{n,s} \beta \, \mathrm{E}_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \left(\frac{n^w_{s,t+1}}{n^w_{s,t}} - 1 \right) \frac{(1+\wedge_{s,t+1})p_{s,t+1}}{p_{t+1}} y_{s,t+1} \left(\frac{n^w_{s,t+1}}{(n^w_{s,t})^2} \right) \right\} \end{aligned} \tag{A.7}$$

$$mpk_{s,t} = \upsilon_s \cdot \alpha_s \cdot \gamma_s \cdot \left(\frac{y_s}{\tilde{k}_s} \right) \left(\frac{y_{s,t}/y_s}{v^p_{s,t}/v^p_s} \right)^{1/\iota} \left(\frac{v^p_{s,t}/v^p_s}{v^b_{s,t}/v^b_s} \right)^{1/\theta} \left(\frac{v^b_{s,t}/v^b_s}{\tilde{k}_{s,t}/\tilde{k}_s} \right)^{1/\phi} \tag{A.8}$$

$$mpl^b_{s,t} = \upsilon_s \cdot \alpha_s \cdot (1-\gamma_s) \cdot \left(\frac{y_s}{n^b_s} \right) \left(\frac{y_{s,t}/y_s}{v^p_{s,t}/v^p_s} \right)^{1/\iota} \left(\frac{v^p_{s,t}/v^p_s}{v^b_{s,t}/v^b_s} \right)^{1/\theta} \left(\frac{v^b_{s,t}/v^b_s}{n^b_{s,t}/n^b_s} \right)^{1/\phi} \tag{A.9}$$

$$mpl^p_{s,t} = \upsilon_s \cdot (1-\alpha_s) \left(\frac{y_s}{n^p_s} \right) \left(\frac{y_{s,t}/y_s}{v^p_{s,t}/v^p_s} \right)^{1/\iota} \left(\frac{v^p_{s,t}/v^p_s}{n^p_{s,t}/n^p_s} \right)^{1/\theta} \tag{A.10}$$

$$mpl^w_{s,t} = (1-\upsilon_s) \cdot \left(\frac{y_s}{n^w_s} \right) \cdot \left(\frac{y_{s,t}/y_s}{n^w_{s,t}/n^w_s} \right)^{1/\iota} \tag{A.11}$$

$$\psi(\pi_{s,t}-1)\pi_{s,t} = \psi\beta\,\mathrm{E}_t\left\{\frac{\lambda_{t+1}}{\lambda_t}\frac{y_{s,t+1}}{y_{s,t}}\frac{\wedge_{s,t+1}}{\wedge_{s,t}}\frac{\pi_{s,t+1}}{\pi_{t+1}}(\pi_{s,t+1}-1)\pi_{s,t+1}\right\} + \epsilon\left(mc_{s,t}-\frac{p_{s,t}}{p_t}\frac{(\epsilon-1)}{\epsilon}\right) \tag{A.12}$$

The first-order conditions of the household problem are given by

$$c_{1,t} = \zeta\left(\frac{(1+\wedge_{1,t})p_{1,t}}{p_t}\right)^{-\mu}c_t \tag{A.13}$$

$$c_{2,t} = (1-\zeta)\left(\frac{(1+\wedge_{2,t})p_{2,t}}{p_t}\right)^{-\mu}c_t \tag{A.14}$$

$$1 = \left(\zeta\cdot\left(\frac{(1+\wedge_{1,t})p_{1,t}}{p_t}\right)^{1-\mu} + (1-\zeta)\cdot\left(\frac{(1+\wedge_{2,t})p_{2,t}}{p_t}\right)^{1-\mu}\right)^{1/(1-\mu)} \tag{A.15}$$

$$n^p_{1,t} = \aleph^p\left(\frac{(1-\wedge^p_t)w^p_{1,t}}{w^p_t}\right)^{\omega}n^p_t \tag{A.16}$$

$$n^p_{2,t} = (1-\aleph^p)\left(\frac{(1-\wedge^p_t)w^p_{2,t}}{w^p_t}\right)^{\omega}n^p_t \tag{A.17}$$

$$n^b_{1,t} = \aleph^b\left(\frac{(1-\wedge^b_t)w^b_{1,t}}{w^b_t}\right)^{\omega}n^b_t \tag{A.18}$$

$$n^b_{2,t} = (1-\aleph^b)\left(\frac{(1-\wedge^b_t)w^b_{2,t}}{w^b_t}\right)^{\omega}n^b_t \tag{A.19}$$

$$n^w_{1,t} = \aleph^w\left(\frac{(1-\wedge^w_t)w^w_{1,t}}{w^w_t}\right)^{\omega}n^w_t \tag{A.20}$$

$$n^w_{2,t} = (1-\aleph^w)\left(\frac{(1-\wedge^w_t)w^w_{2,t}}{w^w_t}\right)^{\omega}n^w_t \tag{A.21}$$

$$w^p_t = \left(\aleph^p\cdot((1-\wedge^p_t)w^p_{1,t})^{1+\omega} + (1-\aleph^p)\cdot((1-\wedge^p_t)w^p_{2,t})^{1+\omega}\right)^{1/(1+\omega)} \tag{A.22}$$

$$w^b_t = \left(\aleph^b\cdot((1-\wedge^b_t)w^b_{1,t})^{1+\omega} + (1-\aleph^b)\cdot((1-\wedge^b_t)w^b_{2,t})^{1+\omega}\right)^{1/(1+\omega)} \tag{A.23}$$

$$w^w_t = \left(\aleph^w\cdot((1-\wedge^w_t)w^w_{1,t})^{1+\omega} + (1-\aleph^w)\cdot((1-\wedge^w_t)w^w_{2,t})^{1+\omega}\right)^{1/(1+\omega)} \tag{A.24}$$

$$\lambda_t = \xi_t + \chi\tilde{\iota}_t\frac{x_t}{c_t} \tag{A.25}$$

$$x_t = c_t^{\chi}x_{t-1}^{1-\chi} \tag{A.26}$$

$$\tilde{\iota}_t = -\xi_t\Omega_t + \beta(1-\chi)\,\mathrm{E}_t\left\{\tilde{\iota}_{t+1}\frac{x_{t+1}}{x_t}\right\} \tag{A.27}$$

$$\Omega_t = \frac{\Omega^p}{1+1/\eta}(n^p_t)^{1+1/\eta} + \frac{\Omega^b}{1+1/\eta}(n^b_t)^{1+1/\eta} + \frac{\Omega^w}{1+1/\eta}(n^w_t)^{1+1/\eta} \tag{A.28}$$

$$\lambda_t = \beta\,\mathrm{E}_t\left\{\lambda_{t+1}\frac{(1+r_t)}{\pi_{t+1}}\right\} \tag{A.29}$$

$$\lambda_t q_{s,t} = \beta\,\mathrm{E}_t\left\{\lambda_{t+1}\left((1-\tau^k_{t+1})r^k_{s,t+1}u_{s,t+1} - \frac{(1+\wedge_{s,t+1})p_{s,t+1}}{p_{t+1}}e(u_{s,t+1}) + q_{s,t+1}(1-\delta)\right)\right\} \tag{A.30}$$

$$\frac{(1+\wedge_{s,t})p_{s,t}}{p_t} = q_{s,t}\left(1-\frac{\kappa_i}{2}\left(\frac{i_{s,t}}{i_{s,t-1}}-1\right)^2-\kappa_i\left(\frac{i_{s,t}}{i_{s,t-1}}-1\right)\frac{i_{s,t}}{i_{s,t-1}}\right)$$
$$+\beta\,\mathrm{E}_t\left\{\frac{\lambda_{t+1}}{\lambda_t}q_{s,t+1}\kappa_i\left(\frac{i_{s,t+1}}{i_{s,t}}-1\right)\left(\frac{i_{s,t+1}}{i_{s,t}}\right)^2\right\} \quad \text{(A.31)}$$

$$(1-\tau_t^k)r_{s,t}^k = \frac{(1+\wedge_{s,t})p_{s,t}}{p_t}\left(\delta_1+\delta_2(u_{s,t}-1)\right) \quad \text{(A.32)}$$

$$w_t^b(1-\tau_t^n)\lambda_t = \Omega^b\left(n_t^b\right)^{1/\eta}x_t\xi_t \quad \text{(A.33)}$$

$$w_t^p(1-\tau_t^n)\lambda_t = \Omega^p\left(n_t^p\right)^{1/\eta}x_t\xi_t \quad \text{(A.34)}$$

$$w_t^w(1-\tau_t^n)\lambda_t = \Omega^w\left(n_t^w\right)^{1/\eta}x_t\xi_t \quad \text{(A.35)}$$

$$\xi_t = (c_t-\Omega_t x_t)^{-\frac{1}{\sigma}} \quad \text{(A.36)}$$

$$k_{s,t} = (1-\delta)k_{s,t-1}+\left(1-\frac{\kappa_i}{2}\left(\frac{i_{s,t}}{i_{s,t-1}}-1\right)^2\right)i_{s,t} \quad \text{(A.37)}$$

$$e(u_{s,t}) = \delta_1(u_{s,t}-1)+\frac{\delta_2}{2}(u_{s,t}-1)^2 \quad \text{(A.38)}$$

where $s=1,2$, and λ_t, $q_{s,t}\lambda_t$, and $\tilde{\iota}_t$ denote Lagrange multipliers on the household's budget constraint, the capital accumulation equations, and the definition of x_t, respectively, where $q_{s,t}$ is the shadow value of installed capital in sector s.

Fiscal and monetary policy are described by

$$\frac{p_{g,t}}{p_t}g_t+T_t+(1+r_{t-1})\frac{b_{t-1}}{\pi_t} = b_t+\tau_t^n\left(w_t^b n_t^b+w_t^p n_t^p+w_t^w n_t^w\right)$$
$$+\tau_t^k\left(r_{1,t}^k\tilde{k}_{1,t}+r_{2,t}^k\tilde{k}_{2,t}\right) \quad \text{(A.39)}$$

$$g_{1,t} = \zeta_g\left(\frac{(1+\wedge_{1,t})p_{1,t}}{p_{g,t}}\right)^{-\mu}g_t \quad \text{(A.40)}$$

$$g_{2,t} = (1-\zeta_g)\left(\frac{(1+\wedge_{2,t})p_{2,t}}{p_{g,t}}\right)^{-\mu}g_t \quad \text{(A.41)}$$

$$\frac{p_{g,t}}{p_t} = \left(\zeta_g\cdot\left(\frac{(1+\wedge_{1,t})p_{1,t}}{p_t}\right)^{1-\mu}+(1-\zeta_g)\cdot\left(\frac{1+\wedge_{2,t})p_{2,t}}{p_t}\right)^{1-\mu}\right)^{1/(1-\mu)} \quad \text{(A.42)}$$

$$\log g_t = (1-\rho_g)\log g+\rho_g\log g_{t-1}+\varepsilon_t^g \quad \text{(A.43)}$$

$$\log(T_t) = (1-\rho_T)\log(T)+\rho_T\log(T_{t-1})-\gamma_b\cdot(b_{t-1}-b)/y \quad \text{(A.44)}$$

$$\tau_t^n-\tau^n = \rho_\tau(\tau_{t-1}^n-\tau^n)+\varepsilon_t^{\tau^n} \quad \text{(A.45)}$$

$$\tau_t^k-\tau^k = \rho_\tau(\tau_{t-1}^k-\tau^k)+\varepsilon_t^{\tau^k} \quad \text{(A.46)}$$

$$\log\left((1+r_t)/(1+r)\right) = \delta_\pi\log(\pi_t/\pi)+\delta_y\log(y_t/y)+\delta_g\log(g_t/g) \quad \text{(A.47)}$$

The following conditions describe goods market clearing for good $s = 1, 2$, inflation in sector s, and aggregate output y_t:

$$\begin{aligned} y_{s,t} = &(1 + \wedge_{s,t}) \Bigg(c_{s,t} + i_{s,t} + g_{s,t} + e(u_{s,t})k_{s,t-1} + \frac{\psi}{2} (\pi_{s,t} - 1)^2 y_{s,t} \\ &+ \frac{\kappa_{n,s}}{2} \left[\left(\frac{n^b_{s,t}}{n^b_{s,t-1}} - 1 \right)^2 + \left(\frac{n^p_{s,t}}{n^p_{s,t-1}} - 1 \right)^2 + \left(\frac{n^w_{s,t}}{n^w_{s,t-1}} - 1 \right)^2 \right] y_{s,t} \Bigg) \\ &+ \frac{p_t}{p_{s,t}} \left(\wedge^p_t w^p_{s,t} n^p_{s,t} + \wedge^b_t w^b_{s,t} n^b_{s,t} + \wedge^w_t w^w_{s,t} n^w_{s,t} \right) \end{aligned} \tag{A.48}$$

$$\pi_{s,t} = \frac{p_{s,t}/p_t}{p_{s,t-1}/p_{t-1}} \pi_t \,, \qquad s = 1, 2 \tag{A.49}$$

$$y_t = (p_{1,t}/p_t) y_{1,t} + (p_{2,t}/p_t) y_{2,t} \tag{A.50}$$

We define data-consistent employment by sector $s = 1, 2$, occupation $o = p, b, w$, as well as aggregate employment as follows:

$$l_{s,t} = \frac{1}{1 + \wedge_{s,t}} \left(n^p_{s,t}(1 - \wedge^p_t) + n^b_{s,t}(1 - \wedge^b_t) + n^w_{s,t}(1 - \wedge^w_t) \right) \,, \tag{A.51}$$

$$l^o_t = (1 - \wedge^o_t) \left(\frac{n^o_{1,t}}{1 + \wedge_{1,t}} + \frac{n^o_{2,t}}{1 + \wedge_{2,t}} \right) \,, \tag{A.52}$$

and

$$l_t = l^w_t + l^b_t + l^p_t = l_{1,t} + l_{2,t}. \tag{A.53}$$

Additional tables

Table A.1: Assignment of NAICS industries to social and distant sector.

Industry	Sector
Agriculture, forestry, fishing and hunting	distant
Mining, quarrying, and oil and gas extraction	distant
Utilities	distant
Construction	distant
Manufacturing	distant
Wholesale trade	distant
Retail trade	social
Transportation and warehousing	
Warehousing and storage	distant
Truck transportation	distant
Pipeline transportation	distant
All other	social
Information	distant
Finance and insurance	distant
Real estate and rental and leasing	social
Professional, scientific, and technical services	distant
Management of companies and enterprises	distant
Administrative and support and waste management and remediation services	distant
Educational services; state, local, and private	social
Healthcare and social assistance	social
Arts, entertainment, and recreation	social
Accommodation and food services	social
Other services (except public administration)	social
Government	n.a.

Source: Kaplan, Moll, and Violante (2020).

Table A.2: Assignment of SOC occupations to white-collar, blue-collar, and pink-collar occupation groups

Occupation	Group
Management occupations	white-collar
Business and financial operations occupations	white-collar
Computer and mathematical occupations	white-collar
Architecture and engineering occupations	white-collar
Life, physical, and social science occupations	white-collar
Community and social service occupations	pink-collar
Legal occupations	white-collar
Education, training, and library occupations	white-collar
Arts, design, entertainment, sports, and media occupations	white-collar
Healthcare practitioners and technical occupations	white-collar
Healthcare support occupations	pink-collar
Protective service occupations	blue-collar
Food preparation and serving related occupations	pink-collar
Building and grounds cleaning and maintenance occupations	pink-collar
Personal care and service occupations	pink-collar
Sales and related occupations	pink-collar
Office and administrative support occupations	white-collar
Farming, fishing, and forestry occupations	blue-collar
Construction and extraction occupations	blue-collar
Installation, maintenance, and repair occupations	blue-collar
Production occupations	blue-collar
Transportation and material moving occupations	blue-collar

Table A.3: Distribution of cumulated employment effects of fiscal policies, alternative calibrations.

	spending expansions									tax cuts								
	$\Delta G_1 = \Delta G_2$			$\Delta G_1 > \Delta G_2$			$\Delta G_1 < \Delta G_2$			$\Delta \tau_l = \Delta \tau_k$			$\Delta \tau_l < 0$			$\Delta \tau_k < 0$		
	social sector	pink-collar	blue-collar	social sector	pink-collar	blue-collar	social sector	pink-collar	blue-collar	social sector	pink-collar	blue-collar	social sector	pink-collar	blue-collar	social sector	pink-collar	blue-collar
Baseline																		
impact	0.67	0.39	0.08	0.84	0.47	0.07	0.38	0.27	0.09	0.69	0.41	0.07	0.64	0.31	0.16	1.06	1.19	-0.64
one year	0.65	0.39	0.11	0.75	0.43	0.10	0.53	0.34	0.11	0.66	0.41	0.10	0.60	0.30	0.20	1.23	1.46	-0.96
four years	0.61	0.38	0.14	0.68	0.41	0.14	0.52	0.35	0.15	0.62	0.40	0.12	0.56	0.29	0.24	1.48	2.00	-1.69
Constant capital utilization																		
impact	0.61	0.22	0.28	0.91	0.32	0.39	0.21	0.09	0.14	0.60	0.22	0.28	0.60	0.22	0.28	0.67	0.21	0.33
one year	0.56	0.21	0.29	0.66	0.24	0.34	0.42	0.17	0.24	0.55	0.21	0.29	0.55	0.21	0.29	0.62	0.15	0.42
four years	0.53	0.21	0.33	0.62	0.24	0.34	0.42	0.18	0.31	0.54	0.24	0.29	0.53	0.23	0.30	2.26	6.81	-7.77
No spending feedback in Taylor rule																		
impact	0.69	0.40	0.08	1.20	0.62	0.06	2.87	1.35	-0.01	0.69	0.41	0.07	0.64	0.31	0.16	1.06	1.19	-0.64
one year	0.68	0.40	0.11	1.07	0.56	0.09	-2.78	-1.04	0.25	0.66	0.41	0.10	0.60	0.30	0.20	1.23	1.46	-0.96
four years	0.64	0.34	0.21	1.03	0.51	0.15	-1.44	-0.54	0.52	0.62	0.40	0.12	0.56	0.29	0.24	1.48	2.00	-1.69
Homogeneous labor adjustment costs																		
impact	0.60	0.36	0.08	0.81	0.46	0.08	0.33	0.23	0.09	0.61	0.37	0.07	0.55	0.28	0.18	1.22	1.37	-1.07
one year	0.60	0.37	0.11	0.71	0.42	0.11	0.47	0.31	0.12	0.61	0.38	0.10	0.54	0.28	0.21	1.42	1.68	-1.36
four years	0.59	0.37	0.15	0.67	0.40	0.14	0.50	0.34	0.15	0.59	0.39	0.12	0.53	0.28	0.25	1.58	2.10	-1.87
Non-zero wealth effect																		
impact	0.68	0.40	0.07	0.88	0.49	0.05	0.35	0.24	0.09	0.72	0.47	0.01	0.64	0.31	0.15	1.51	2.13	-1.48
one year	0.66	0.41	0.09	0.79	0.47	0.08	0.51	0.34	0.10	0.71	0.49	0.01	0.61	0.30	0.19	2.13	3.17	-2.66
four years	0.62	0.41	0.11	0.73	0.45	0.10	0.50	0.36	0.12	0.67	0.50	0.00	0.56	0.30	0.24	3.48	5.74	-5.91
Reduced price stickiness																		
impact	0.70	0.41	0.09	0.91	0.49	0.06	-0.65	-0.10	0.22	0.71	0.42	0.07	0.65	0.31	0.17	1.18	1.32	-0.70
one year	0.67	0.40	0.11	0.83	0.46	0.10	0.28	0.26	0.15	0.66	0.41	0.10	0.61	0.31	0.20	1.22	1.42	-0.89
four years	0.62	0.37	0.16	0.77	0.43	0.14	0.35	0.27	0.20	0.62	0.40	0.12	0.56	0.30	0.24	1.34	1.73	-1.37

Notes: Table shows sector-specific and occupation-specific shares in the cumulated employment difference between pandemic scenarios with and without fiscal intervention. First column shows horizon with "impact" referring to the quarter where the fiscal intervention begins ($t = 4$) and "one year" and "four year" referring to the time span from the start of the intervention, i.e., $t = 4$ through $t = 8$ and $t = 4$ through $t = 20$, respectively. "Non-zero wealth effect" calibration uses $\xi = 1$. "Reduced price stickiness" calibration uses price adjustment cost parameter equivalent to price adjustments every six months.