

# The Coronavirus Stimulus Package: How large is the transfer multiplier?\*

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## Abstract

In response to the COVID-19 pandemic, large parts of the economy were locked down and, as a result, households' income risk rose sharply. At the same time, policy makers put forward the largest stimulus package in history. In the U.S., it amounted to \$2 trillion, a quarter of which represented transfer payments to households. To the extent that such transfers were i) announced in advance and ii) conditional on recipients being unemployed, they mitigated income risk associated with the lockdown—in contrast to unconditional transfers. We develop a baseline scenario for a COVID-19 recession in a medium-scale HANK model and use counterfactuals to quantify the impact of transfers. For the short run, we find large differences in the transfer multiplier: it is negligible for unconditional transfers and about unity for conditional transfers. Overall, we find that the transfers reduced the output loss due to the pandemic by some 2 percentage points at its trough.

*Keywords:* COVID-19, Coronavirus, CARES Act, fiscal policy, stimulus, conditional transfer, transfer multiplier, lockdown, quarantine

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# 1 Introduction

The economic fallout of the COVID-19 pandemic was unprecedented. As many businesses and industries were locked down in an effort to limit infections—either voluntarily or by government mandate—unemployment rose sharply. In the ten weeks from mid-March to the end of May 2020 some 40 million initial claims to unemployment benefits were filed in the U.S. The left panel of Figure 1 shows time-series data, testifying to the exceptional nature of the labor-market developments during the pandemic. A similar picture emerges for the unemployment rate, shown in the right panel. As a result, the COVID-19 pandemic raised income risk for U.S. households strongly—much more so than in a usual recession.<sup>1</sup>

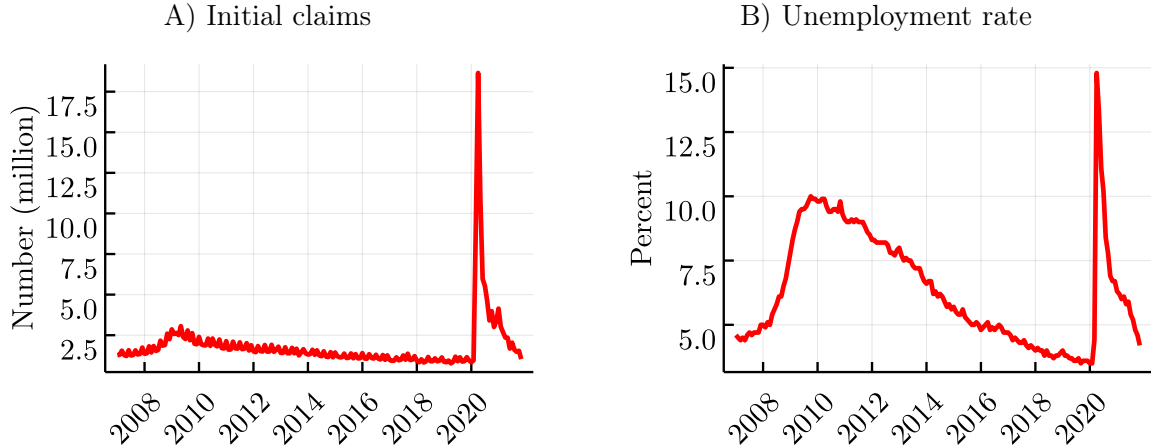
The pandemic also triggered an exceptional fiscal response.<sup>2</sup> On March 27, 2020 former President Trump signed the Coronavirus Aid, Relief, and Economic Security (CARES) Act into law. As a result, \$2 trillion of federal funds were disbursed to households and firms through various channels. The largest items on the household side included, first, a one-time payment of \$1,200 to any adult in the U.S. population with a gross income of up to \$75,000 and, second, a top up to state unemployment benefits of \$600 per week. Under the Federal Pandemic Unemployment Compensation (FPUC) scheme, the unemployed received this sum irrespective of their earlier earnings up until the end of July 2020. Each of these measures triggered additional federal expenditures of some \$270 billion. To put this into perspective, recall that the entire American Recovery and Reinvestment Act (ARRA), legislated in 2009 in response to the financial crisis, mobilized some \$800 billion of federal spending.

In this paper, we analyze the quantitative impact of the transfer components of the CARES Act and assess to what extent they limited the economic fallout from the COVID-19 pandemic. We proceed in two steps. First, we develop a baseline scenario for the COVID-19 recession. For this purpose, we specify a “quarantine shock,” or “Q-shock” for short. Importantly, we abstract entirely from the epidemiological causes that underlie this shock in order to focus on the efficacy of transfers during the COVID-19 recession. Moreover, we are completely agnostic as to whether the Q-shock is imposed by governments or the result of voluntary social restraint: What matters is that as a result of the shock a sizeable fraction of the labor force is locked out of/prefers not to/cannot work for health reasons. In addition, a fraction of the aggregate capital stock and the goods of some sectors also become

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<sup>1</sup>Initially, some observers suggested that unemployment would reach 30% in the second quarter of 2020; see, for instance, the remark by the president of the Federal Reserve Bank of St. Louis, James Bullard, reported by Bloomberg on March 22, 2020, or Faria-e-Castro (2020).

<sup>2</sup>The Federal Reserve, too, took a series of measures in response to the COVID-19 crisis, including cutting its policy rate to zero. In our analysis, we account for Fed policy but our focus is on the fiscal response to the crisis. Assuming uninsurable income risk, Wolf (2021) establishes conditions under which fiscal stimulus can be a perfect substitute for interest rate cuts.



**Figure 1:** Unemployment. Notes: Panel A) monthly initial claims to unemployment benefits; Panel B) monthly unemployment rate, both from 2007–2021. Source: FRED Economic Data, St. Louis Fed.

temporarily unavailable for production and consumption. As a result, the shock not only lowers the production potential of the aggregate economy, it also triggers an unprecedented increase in income risk at the household level, which, in turn, induces the private sector to increase savings. In the baseline, we assume that the Q-shock is fully anticipated. This is a conservative assumption because unemployment recovers more quickly in May 2020 than in previous recessions. While income risk rises sharply, our baseline thus assumes households to know the increase to be of very limited duration.<sup>3</sup>

Second, we study model-based counterfactuals and investigate how the Coronavirus stimulus shaped the COVID-19 recession. We focus on the transfer payments which households receive in the baseline, both unconditional transfers and transfers that are conditional on the recipient being unemployed.<sup>4</sup> Unconditional transfers are part of the recession-fighting toolkit and have been deployed before. The Economic Stimulus Act passed in February 2008 under the Bush administration, for instance, was a \$100 billion program under which taxpayers received a \$900 payment (Broda and Parker, 2014). The economic rationale is straightforward: to the extent that households are liquidity or credit constrained, they will

<sup>3</sup>We also study an alternative scenario where anticipation of the Q-shock is incomplete since, in some respects, the pandemic took firms by surprise (Hassan et al., 2021). Also, beliefs about the duration of the lockdown varied widely among firms and households (Bartik et al., 2020; Dietrich et al., 2022). Moser and Yared (2022) analyze the role of government commitment to the extent of future lockdowns. According to their analysis, lack of commitment leads to more severe lockdowns and larger losses in output and consumption.

<sup>4</sup>There is also an element of conditionality in the \$1,200 payment per person under the CARES Act, but this concerns only a small fraction of the population. We account for this in our model simulations but refer to it as an “unconditional transfer” for simplicity.

spend the largest part of the transfer, even if taxes may go up at some point in the future. This, in turn, may limit the reduction of private expenditure triggered by the recession. By targeting the unemployed, conditional transfers provide more funds per recipient for a fiscal package of a given size. On top of this, they lower income risk associated with becoming unemployed and thus the need for precautionary savings in response to the Q-shock.

We conduct our analysis within a heterogeneous agent New Keynesian (HANK) model, put forward and estimated by Bayer et al. (2020, 2021). It is particularly well suited for the purpose at hand because it features income risk: households face different labor market outcomes and, because financial markets are incomplete, the resulting income risk is not shared across households. The model also features various additional frictions and is able to account for key features of the business cycle. We find that the calibrated version of the model that we use in this paper also captures key aspects of the COVID-19 recession—both along the time-series dimension and in terms of the heterogeneity of labor market outcomes in the cross-section of households. The model predicts the evolution of key macroeconomic indicators during the period 2020/21 quite accurately, even though—with the exception of the unemployment rate—they are not targeted in the calibration of the model. It also accounts well for the incidence and dynamics of unemployment across the income distribution.

We compute the quantitative effect of the CARES transfers through model-based counterfactuals. Absent the transfers, the collapse of economic activity which amounts to about 10 percent in the baseline would have been larger by almost 2 percentage points at its trough. Also, because the recovery would have been slower without transfers, the cumulative output loss would have been larger by about 13 percent of monthly GDP. This effect is largely due to conditional transfers. To illustrate this, we compute the cumulative transfer multiplier. In the short run it is about 0.25 for the overall transfer component of the CARES act, but about 1 for conditional transfers and basically 0 for unconditional transfers. Conditional transfers are effective in stabilizing the economy because they are targeted to households with the highest marginal propensity to consume and because they lower income risk.

We also study the distributional consequences and the welfare effects of the Q-shock and the transfer payments. The results are clear cut. The COVID-19 recession led to an increase in inequality across a range of indicators, but the transfers dampened this effect to a considerable extent. A similar picture emerges for welfare. While the pandemic had adverse welfare effects across all wealth groups, they were particularly strong for the poor. The transfers under the CARES act, in turn, were very effective in offsetting these effects. And while we do not offer a full-fledged analysis of the optimal fiscal response to the pandemic, our simulations show that there are decreasing returns to the transfer payments in terms of macroeconomic stabilization because of the way they interact with income risk.

The paper is organized as follows. In the remainder of the introduction we clarify the paper’s main message and its connection to the existing literature. Section 2 outlines the model structure. Section 3 explains in detail our parameter choices. We present our results in Section 4, zooming in on the transmission mechanism of both, the Q-shock and the alternative transfer instruments. A final section offers some conclusions.

**Related literature.** Our model extends the framework of Bayer et al. (2020, 2021), first, by introducing two new labor market states. In this way we account for the fact that workers face the risk of not being able to work, be it because of sickness, actual quarantine, or more general lockdowns. Second, we assume that also product varieties as well as the capital stock used in production are “quarantined” in the same way and temporarily unavailable for consumption and production. Third, we model the actual fiscal transfers that were legislated in response to the pandemic. Additionally, we calibrate monetary policy to match the observed path of interest rates instead of using estimated monetary policy rules from pre-pandemic times. Also, rather than allowing for an array of shocks to hit the economy, we focus on the unique circumstances of the COVID-19 pandemic. These modifications are important because we want the model to account for short-term unemployment risk and fluctuations in product varieties as drivers of the recession and to study targeted transfers which have been absent from previous work.

Related work by, among others, Guerrieri et al. (2022) and Kaplan et al. (2020), share with our work some of these features. Specifically, the notion that the limited availability of product varieties are important to understand inflation and business cycle dynamics during the COVID-19 recession is due to Guerrieri et al. (2022). Moving beyond their work, we embed this aspect in a quantitative DSGE model that also features household heterogeneity. Similar to Kaplan et al. (2020), we show that it is important to consider heterogeneity at the household level to understand the full consequences of the COVID-19 pandemic. The focus on the role of different types of transfers distinguishes our work from theirs. Our findings suggest that both the demand shortages due to temporarily unavailable products and services and the sharp increase in income risk are important to understand the COVID-19 recession. In particular the sharp rise in income risk is what makes additional insurance provided by the CARES package individually valuable for affected households and gives rise to additional aggregate stabilization.

A more conventional model would not allow us to capture the workings of CARES transfers correctly. This holds true, in particular, for “two-agent New Keynesian” (TANK) models. Coenen et al. (2012), for instance, offer a systematic analysis of transfer multipliers in seven large-scale TANK models. They find that transfers targeted to liquidity constrained house-

holds can give rise to sizeable multipliers provided the zero lower bound binds, a result further refined in later work (Bilbiie et al., 2013; Giambattista and Pennings, 2017; Mehrotra, 2018; Bilbiie, 2020; Faria-e-Castro, 2022). TANK models have also been used to study the transfers during the COVID-19 recession. Faria-e-Castro (2021) finds that the unemployment-benefits multiplier is larger during the COVID-19 recession than in normal times. Bhattarai et al. (2021) show that the transfer multiplier depends on the monetary-fiscal mix.<sup>5</sup> Importantly, TANK models do not account for household income risk which is at the core of our analysis.

Yet there is work which considers incomplete markets and income risk while studying the transfer multiplier. Oh and Reis (2012) perform a quantitative analysis of the transfers of the ARRA package in a model with household heterogeneity and sticky information. They find very small transfer multipliers on output, even though they assume that transfers are targeted to households with a high marginal propensity to consume. Likewise McKay and Reis (2016) and Hagedorn et al. (2019) obtain moderate tax and transfer multipliers in calibrated versions of one-asset HANK models. Moving beyond these papers, we model wealthy-hand-to-mouth households as introduced by Kaplan and Violante (2014). They show in partial equilibrium that illiquid wealth can rationalize sizable consumption responses to transfers and low levels of consumption insurance. By using a similar setup in a New Keynesian model, the distinct contribution of our analysis is to show that conditional transfers in deep recessions lower income risk and thereby generate sizeable multiplier effects, in line with earlier work on unemployment benefits as automatic stabilizers (Ravn and Sterk, 2017; Den Haan et al., 2017; McKay and Reis, 2021; Kekre, 2022).

We believe that some of our results, such as the effectiveness of counter-cyclical unemployment benefits, are fairly general and may inform the government response to other recessions. On the other hand, some of our results, including those related to products and services becoming temporarily unavailable are specific to the COVID-19 recession because they are due to measures that are meant to protect individual or public health. In order to explore potential trade-offs between health protection and economic welfare, a number of studies develop explicit microfoundations of the interaction between economic activity and infection dynamics (Eichenbaum et al., 2021; Glover et al., 2021; Boppart et al., 2020). Instead, because we consider our model as a laboratory to study the properties of alternative fiscal transfers, we account for the feedback from economic activity to the state of the pandemic via a straightforward reduced-form relationship.

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<sup>5</sup>In related work, Auerbach et al. (2021) put forward a stylized model with COVID-19-related restrictions and economic slack. They show analytically that transfers to low-income households can increase spending on unrestricted items and that targeted transfers to firms are particularly effective in stimulating the economy.

## 2 Model

The model and our exposition here closely follow Bayer et al. (2020, 2021), extended to capture the economic fallout from the COVID-19 pandemic. We use the same general setup for the economy: it is composed of a firm sector, a household sector, and a government sector. In the firm sector, we define several layers in order to maintain tractability. There is a continuum of isomorphic final-good sectors, each characterized by monopolistic competition. Final good producers rely on homogeneous intermediate inputs provided by perfectly competitive intermediate goods producers. Capital goods, in turn, are produced on the basis of final goods, subject to adjustment costs. Labor services are assembled on the basis of differentiated labor types provided by unions that, in turn, differentiate the raw labor input of households. Price setting for the final goods as well as wage setting by unions is subject to nominal rigidities. Households earn income from supplying (raw) labor and capital, and from owning the firm sector, absorbing all of its rents that stem from the market power of unions and final goods producers, and decreasing returns to scale in capital goods production. The government sector runs both a fiscal authority and a monetary authority. The fiscal authority levies taxes on labor income and distributed pure profits (monopoly rents), issues government bonds, and adjusts expenditures to stabilize debt in the long run. The monetary authority sets the nominal interest rate on government bonds according to a Taylor rule targeting inflation and output growth.

To study the pandemic, we add short term unemployment risk, unemployment insurance, and transfers to the model of Bayer et al. (2020), but, most importantly, we introduce the idea of “quarantines”, the  $Q$ -shock. Quarantines imply that a fraction of the workforce, a fraction of the capital stock, and a fraction of sectors, can no longer supply their services, be it because of a government mandated lockdown, be it because of actual infections, or be it because consumers shy away from demanding the services to avoid infections themselves. This creates a recession environment that is characterized by a shortage of factor supplies, an increase in individual income risks and, as explained in detail by Guerrieri et al. (2022), by Keynesian supply shocks. These demand spillovers across sectors depend crucially on the elasticity of substitution across the goods produced in different sectors. Hence, we allow it to differ from the elasticity of substitution within sectors.

### 2.1 Households

The household sector is subdivided into two types of agents: workers and entrepreneurs. The transition between both types is stochastic. Both rent out physical capital, but only workers supply labor. The efficiency of a worker’s labor evolves randomly, exposing worker-

households to labor-income risk. Entrepreneurs do not work, but earn all pure rents in our economy except for the rents of unions, which are equally distributed across workers. All households self-insure against the income risks they face by saving in a liquid nominal asset (bonds) and a less liquid asset (capital). Trading illiquid assets is subject to random participation in the capital market.

To be specific, there is a continuum of ex-ante identical households of measure one, indexed by  $i$ . Households are infinitely lived, have time-separable preferences with discount factor  $\beta$ , and derive felicity from consumption  $c_{it}$  and leisure. They obtain income from supplying labor,  $n_{it}$ , from renting out capital,  $k_{it}$ , from earning interest on bonds,  $b_{it}$ , and, potentially, from unemployment benefits, firm profits, or union transfers. Households pay taxes on labor and profit income.

A key economic aspect of the pandemic is that, beyond usual levels of unemployment, a substantially larger fraction of workers is locked out of work. We capture this in our model by having, next to a regular unemployment state, a COVID unemployment state; a “quarantine”. To model the aggregate shock to the economy, we let the probability of entering this state vary over time and calibrate it to be a very rare state in the steady state.

### 2.1.1 Productivity, Labor Supply and Labor Income

A household’s endowment with human capital is described in two dimensions. Its underlying productivity  $h$  and whether the household is either employed ( $e = \mathcal{E}$ ), regularly unemployed ( $e = \mathcal{U}$ ), or in COVID-unemployment, in “quarantine” ( $e = \mathcal{Q}$ ).<sup>6</sup> Transitions in productivity evolve according to a first-order Markov chain with transition matrix  $\Pi_h$ . This transition matrix approximates a log-AR(1) process,  $h_{it} = \exp(\rho_h \log h_{it-1} + \epsilon_{it}^h)$ . Transitions between employment and unemployment are determined by the transition matrix

$$\Pi_e = \begin{matrix} & \mathcal{E} & \mathcal{Q} & \mathcal{U} \\ \mathcal{E} & \left( 1 - p_{q,t}^{in}(h) - p_u^{in} \right. & p_{q,t}^{in}(h) & p_u^{in} \\ \mathcal{Q} & \left. p_q^{out,\mathcal{E}} \right. & 1 - p_q^{out,\mathcal{E}} - p_q^{out,\mathcal{U}} & p_q^{out,\mathcal{U}} \\ \mathcal{U} & \left. p_u^{out} \right. & 0 & 1 - p_u^{out} \end{matrix} \Bigg). \quad (1)$$

The probability to enter quarantine is time-varying  $p_{q,t}^{in}(h)$  and depends on the productivity of the household to capture the heterogeneous incidence of job losses across the income

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<sup>6</sup>In absence of a better word, we choose to name the COVID-unemployment state “quarantine”. It summarizes literal quarantine/sickness, lockdown measures and voluntary consumption restraints that render certain activities impossible. The key features of this state are two: First, it captures the additional non-employment effects on factors and sectors of the pandemic and, second, FPUC payments are targeted and limited to workers in that state, which also limits them in time.



distribution (Mongey et al., 2021), given by a logistic function  $\Phi(h)$  with  $\mathbb{E}(\Phi(h)) = 1$ . The process for the probability to enter quarantine is given by

$$p_{q,t}^{in}(h) = p_{q,ss}^{in} + \Phi(h)Q_t, \quad Q_t = \rho_Q Q_{t-1} + \Sigma_{Q,Y} \log(Y_t/\bar{Y}) + \epsilon_t^Q, \quad (2)$$

where  $Q_t$  is the mean-zero probability shifter for quarantines. This shifter follows an AR-1 process with autocorrelation  $\rho_Q$  and innovations  $\epsilon_t^Q$ . It also reacts to deviations of output,  $Y_t$ , from the steady state,  $\bar{Y}$ , captured by the coefficient  $\Sigma_{Q,Y}$ .

The entry into unemployment  $p_u^{in}$  and the exit probabilities,  $p_q^{out,\mathcal{E}/\mathcal{U}}$  and  $p_u^{out}$ , are time-constant. From quarantine, the  $\mathcal{Q}$ -state, workers can go back to employment,  $\mathcal{E}$ , with probability  $p_q^{out,\mathcal{E}}$  or become regularly unemployed,  $\mathcal{U}$ , with probability  $p_q^{out,\mathcal{U}}$ .

The regular unemployed obtain unemployment benefits according to the US unemployment system which has a constant replacement rate that is, however, capped at 50% of the median income. The ‘‘quarantined’’ workers obtain an additional unemployment benefit on top of the payments received in the  $\mathcal{U}$ -state, as described in Section 4.1. Employed households earn gross labor income  $w_t n_{it} h_{it}$ . Some employed households become entrepreneurs with fixed probability  $\zeta$  and return to the median employed state with probability  $\iota$ . An entrepreneur obtains a fixed share of the pure rents (aside from union rents),  $\Pi_t^F$ , in the economy (from monopolistic competition in the goods sector and the creation of capital).<sup>7</sup> We assume that the claim to the pure rents cannot be traded as an asset. Union rents,  $\Pi_t^U$ , are distributed lump-sum across workers, leading to labor-income compression.

With respect to leisure and consumption, households have GHH preferences (Greenwood et al., 1988) and maximize the discounted sum of felicity:<sup>8</sup>

$$\mathbb{E}_0 \max_{\{c_{it}, n_{it}\}} \sum_{t=0}^{\infty} \beta^t u [c_{it} - G(h_{it}, n_{it})]. \quad (3)$$

The maximization is subject to the budget constraints described further below. The felicity function  $u$  exhibits a constant relative risk aversion (CRRA) with risk aversion parameter  $\xi > 0$ ,  $u(x_{it}) = \frac{x_{it}^{1-\xi} - 1}{1-\xi}$ , where  $x_{it} = c_{it} - G(h_{it}, n_{it})$  is household  $i$ ’s composite demand for goods consumption  $c_{it}$  and leisure and  $G$  measures the disutility from work. The consumption good is a bundle of varieties  $j$  of differentiated goods from a continuum of final-good

<sup>7</sup>In the steady state, entrepreneurs are wealthy households and as such have a low MPC. Therefore, the assumption is very similar to the one made in TANK models, such as Bilbiie (2020), and increases business cycle propagation somewhat, along the lines discussed there.

<sup>8</sup>The assumption of GHH preferences is motivated by the fact that many estimated DSGE models of business cycles find small aggregate wealth effects in the labor supply; see, e.g., Born and Pfeifer (2014). Bayer et al. (2020) find the same for their HANK model when comparing the marginal likelihood of the model with GHH and KPR preferences.

sectors  $k$  of measure one. Formally, we rely on a nested Dixit-Stiglitz aggregator:

$$c_{it} = \left[ \int \psi_{kt} \left( \int_{j \in S(k)} c_{ijkt}^{\frac{\eta_F-1}{\eta_F}} dj \right)^{\frac{\eta_F-1}{\eta_F-1} \frac{\eta_S-1}{\eta_S}} dk \right]^{\frac{\eta_S}{\eta_S-1}}, \quad (4)$$

where  $j \in S(k)$  indicates that differentiated good  $j$  belongs to sector  $k$ . The elasticity of substitution within a final-good sector,  $\eta_F$ , is assumed to be larger than the substitutability across sectors,  $\eta_S$ . Each of the differentiated goods,  $j$ , is offered at price  $p_{jt}$ . Not all sectors are equally affected by the pandemic. We model this by the indicator  $\psi$  which determines whether sector- $k$  goods can actually be bought ( $\psi_{kt} = 1$ ) or become unavailable due to the pandemic ( $\psi_{kt} = 0$ ). This means that the demand for each of the varieties is given by

$$c_{ijkt} = \psi_{kt} \left( \frac{p_{jt}}{P_{kt}} \right)^{-\eta_F} c_{ikt}. \quad (5)$$

Here  $P_{kt}$  is the (ideal) price index of all varieties in sector  $k$  and using these prices, we obtain the aggregate price level  $P_t = \left( \int \psi_{kt} P_{kt}^{1-\eta_S} dk \right)^{\frac{1}{1-\eta_S}}$ .

Without further loss of generality, we can normalize the disutility of labor:  $G(h_{it}, n_{it}) = h_{it} \frac{n_{it}^{1+\gamma}}{1+\gamma}$ . This simplifies the household problem as  $h_{it}$  drops out from the first-order condition. All employed households supply the same number of hours  $n_{it} = N(w_t)$ , and income and productivity risk are the same. We denote by  $\bar{H}_t$  the total number of active workers  $\int \mathbb{I}_{e_{it}=\mathcal{E}} di$ . We assume that the same fraction,  $\bar{H}_t$ , of final-good sectors and capital is active, too. For the total effective labor supply, we need to take heterogeneity into account, and obtain this as  $N(w_t)H_t$ , where  $H_t := \int \mathbb{I}_{e_{it}=\mathcal{E}} h_{it} di$  is the productivity weighted share of active workers.

### 2.1.2 Consumption, Savings, and Portfolio Choice

Given the preferences and the stochastic environment above, a household optimizes intertemporally subject to its budget constraint:

$$\begin{aligned} c_{it} + b_{it+1} + q_t k_{it+1} &= b_{it} \frac{R(b_{it}, R_t^b)}{\pi_t} + (q_t + r_t) k_{it} + \mathcal{T}_t(h_{it}) \\ &+ (1 - \tau) [\mathcal{R}(h_{it}, e_{it})(h_{it} w_t N_t + \mathbb{I}_{h_{it} \neq 0} \Pi_t^U) + \mathbb{I}_{h_{it}=0} \Pi_t^F], \\ k_{it+1} &\geq 0, \quad b_{it+1} \geq \underline{B}, \end{aligned} \quad (6)$$

where  $\Pi_t^U$  is union profits,  $\Pi_t^F$  is firm profits,  $b_{it}$  is real bond holdings,  $k_{it}$  is the amount of illiquid assets,  $q_t$  is the price of these assets,  $r_t$  is their dividend,  $\pi_t = \frac{P_t - P_{t-1}}{P_{t-1}}$  is realized inflation, and  $R$  is the nominal interest rate on bonds, which depends on the portfolio position of the household and the central bank's interest rate  $R_t^b$ , which is set one period before. All

households that do not participate in the capital market ( $k_{it+1} = k_{it}$ ) still obtain dividends and can adjust their bond holdings. Depreciated capital has to be replaced for maintenance, such that the dividend,  $r_t$ , is the net return on capital. Holdings of bonds have to be above an exogenous debt limit  $\underline{B}$ , and holdings of capital have to be non-negative.  $\mathcal{R}(h_{it}, e_{it})$  is equal to one for employed ( $e = \mathcal{E}$ ) households, less than one for unemployed ( $e = \mathcal{U}$ ), and can exceed one for quarantined households ( $e = \mathcal{Q}$ ). In line with the U.S. unemployment insurance during the pandemic, the replacement rate depends on the level of forgone income and the CARES payments. Depending on their income level, households potentially receive a lump-sum transfer  $\mathcal{T}_t(h_{it})$ . The tax rate  $\tau$  is constant.

Households make their savings choices and their portfolio choice between liquid bonds and illiquid capital in light of a capital market friction that renders capital illiquid because participation in the capital market is random and i.i.d. in the sense that only a fraction,  $\lambda$ , of households is selected to be able to adjust their capital holdings in a given period.

This leaves us with three functions that characterize the household's problem: value function  $V^a$  for the case where the household adjusts its capital holdings, the function  $V^n$  for the case in which it does not adjust, and the expected envelope value,  $\mathbb{E}V$ , over both:

$$\begin{aligned}
V_t^a(b, k, h, e) &= \max_{k', b'_a} u[x(b, b'_a, k, k', h, e)] + \beta \mathbb{E}_t V_{t+1}(b'_a, k', h', e') \\
V_t^n(b, k, h, e) &= \max_{b'_n} u[x(b, b'_n, k, k, h, e)] + \beta \mathbb{E}_t V_{t+1}(b'_n, k, h', e') \\
\mathbb{E}_t V_{t+1}(b', k', h', e') &= \mathbb{E}_t [\lambda V_{t+1}^a(b', k', h', e')] + \mathbb{E}_t [(1 - \lambda) V_{t+1}^n(b', k, h', e')]
\end{aligned} \tag{7}$$

Expectations about the continuation value are taken with respect to all stochastic processes conditional on the current states. Maximization is subject to the budget constraint.

## 2.2 Firm Sector

The firm sector consists of four sub-sectors: (a) a labor sector composed of “unions” that differentiate raw labor and labor packers who buy differentiated labor and then sell labor services to intermediate goods producers, (b) intermediate goods producers who hire labor services and rent out capital to produce goods, (c) final goods producers who differentiate intermediate goods and then sell them to goods bundlers, who finally sell them as consumption goods to households, and to (d) capital goods producers, who turn bundled final goods into capital goods.

When profit maximization decisions in the firm sector require intertemporal decisions (i.e., in price and wage setting and in producing capital goods), we assume for tractability that they are delegated to a mass-zero group of households (managers) that are risk neutral

and compensated by a share in profits.<sup>9</sup> They do not participate in any asset market and have the same discount factor as all other households. Since managers are a mass-zero group in the economy, their consumption does not show up in any resource constraint and all but the unions' profits go to the entrepreneur households (whose  $h = 0$ ). Union profits go lump sum to worker households.

### 2.2.1 Labor Packers and Unions

Worker households sell their labor services to a mass-one continuum of unions indexed by  $j$ , each of which offers a different variety of labor to labor packers who then provide labor services to intermediate goods producers. Labor packers produce final labor services according to the production function

$$N_t = \left( \int \hat{n}_{jt}^{\frac{\eta_W-1}{\eta_W}} dj \right)^{\frac{\eta_W}{\eta_W-1}}, \quad (8)$$

out of labor varieties  $\hat{n}_{jt}$ . Only a fraction  $H_t$  of these workers finds themselves able to work, because, productivity weighted,  $(1 - H_t)$  is quarantined. Cost minimization by labor packers implies that each variety of labor, each union  $j$ , faces a downward-sloping demand curve

$$\hat{n}_{jt} = \left( \frac{W_{jt}}{W_t^F} \right)^{-\eta_W} N_t, \quad (9)$$

where  $W_{jt}$  is the *nominal* wage set by union  $j$  and  $W_t^F$  is the nominal wage at which labor packers sell labor services to final goods producers.

Since unions have market power, they pay the households a wage lower than the price at which they sell labor to labor packers. Given the nominal wage  $W_t$  at which they buy labor from households and given the *nominal* wage index  $W_t^F$ , unions seek to maximize their discounted stream of profits. However, they face a Calvo-type (1983) adjustment friction (with indexation) with the probability  $\lambda_w$  to keep wages constant. They therefore maximize

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \lambda_w^t \frac{W_t^F}{P_t} N_t H_t \left\{ \left( \frac{W_{jt} \bar{\pi}_W^t}{W_t^F} - \frac{W_t}{W_t^F} \right) \left( \frac{W_{jt} \bar{\pi}_W^t}{W_t^F} \right)^{-\eta_W} \right\}, \quad (10)$$

by setting  $W_{jt}$  in period  $t$  and keeping it constant except for indexation to  $\bar{\pi}_W$ , the steady-state wage inflation rate.

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<sup>9</sup>Since we solve the model by a first-order perturbation in aggregate shocks, the assumption of risk-neutrality only serves as a simplification in terms of writing down the model as managers do not face idiosyncratic income risks. With a first-order perturbation, we have certainty equivalence for aggregate fluctuations, rendering stochastic discount factors of agents constant whose borrowing constraints or idiosyncratic risks do not change.

Since all unions are symmetric, we focus on a symmetric equilibrium and obtain the linearized wage Phillips curve from the corresponding first-order condition as follows, leaving out all terms irrelevant at a first-order approximation around the stationary equilibrium:

$$\log\left(\frac{\pi_t^W}{\bar{\pi}_W}\right) = \beta \mathbb{E}_t \log\left(\frac{\pi_{t+1}^W}{\bar{\pi}_W}\right) + \kappa_w \left(\frac{w_t}{w_t^F} - \frac{1}{\mu^W}\right), \quad (11)$$

with  $\pi_t^W := \frac{W_t^F}{W_{t-1}^F} = \frac{w_t^F}{w_{t-1}^F} \pi_t^Y$  being wage inflation,  $w_t$  and  $w_t^F$  being the respective *real* wages for households and firms, and  $\frac{1}{\mu^W} = \frac{\eta_W - 1}{\eta_W}$  being the target mark-down of wages the unions pay to households,  $W_t$ , relative to the wages charged to firms,  $W_t^F$ , and  $\kappa_w = \frac{(1-\lambda_w)(1-\lambda_w\beta)}{\lambda_w}$ .

### 2.2.2 Final Goods Producers

Similar to unions, final goods producers differentiate a homogeneous intermediate good and set prices. Each reseller  $j$  in sector  $k$  faces a downward-sloping demand curve

$$y_{jt} = \psi_{kt} (p_{jt}/P_{kt})^{-\eta_F} Y_{kt} \quad (12)$$

and buys the intermediate good at the nominal price  $MC_t$ . As we do for unions, we assume price adjustment frictions à la Calvo (1983) with indexation. We assume for simplicity that it is i.i.d. whether a sector is active or not and that this shock realizes after price setting.

Under this assumption, the firms' managers maximize the present value of real profits given this price adjustment friction, i.e., they maximize:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \lambda_Y^t (1 - \tau_t) Y_{kt} \psi_{jt} \left\{ \left( \frac{p_{jt} \bar{\pi}^t}{P_t} - \frac{MC_t}{P_t} \right) \left( \frac{p_{jt} \bar{\pi}^t}{P_t} \right)^{-\eta_F} \right\}, \quad (13)$$

with a time constant discount factor, where  $1 - \lambda_Y$  is the probability of price adjustment and  $\bar{\pi}$  is the steady-state inflation rate.

Since all sectors are symmetric and sectors are shut down randomly after price setting, all firms choose the same price when resetting it. Therefore, all sectoral price levels  $P_{kt} = \left( \int_{j \in S(k)} p_{jt}^{1-\eta_F} dj \right)^{\frac{1}{1-\eta_F}}$  are the same and we denote this price level by  $P_{kt} = P_t^F$ . Yet, it implies a loss in final consumption to the households that only the fraction of sectors can actually offer their varieties ( $\psi_{kt} = 1$ ). This fraction is same as the fraction of workers in  $\mathcal{E}$ ,  $\bar{H}_t$ . Consumers lose out on varieties and this introduces a wedge  $\bar{H}_t^{\frac{1}{1-\eta_S}}$  between the average price set by all firms,  $P_t^F$ , and the effective  $P_t$  of the consumption aggregate (the ideal price index):  $P_t = P_t^F \bar{H}_t^{\frac{1}{1-\eta_S}}$ . Vice versa, it implies that the real value of total output  $Y_t$  is by factor  $\bar{H}_t^{\frac{1}{\eta_S-1}}$  smaller than the quantity of intermediate goods produced.

We use this expression for the relationship between the average price of goods and the effective price level to rewrite the maximization problem of price setters as:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \lambda_Y^t (1 - \tau_t) Y_t \psi_{jt} \bar{H}_t^{\frac{1}{\eta_S - 1}} \left\{ \left( \frac{p_{jt} \bar{\pi}^t}{P_t^F} - \frac{MC_t}{P_t} \frac{1}{\bar{H}_t^{\frac{1}{\eta_S - 1}}} \right) \left( \frac{p_{jt} \bar{\pi}^t}{P_t^F} \right)^{-\eta_F} \right\}, \quad (14)$$

which, through its corresponding first-order condition for price setting, implies a Phillips curve for the average price

$$\log \left( \frac{\pi_t^F}{\bar{\pi}} \right) = \beta \mathbb{E}_t \log \left( \frac{\pi_{t+1}^F}{\bar{\pi}} \right) + \kappa_Y \left( mc_t / \bar{H}_t^{\frac{1}{\eta_S - 1}} - \frac{1}{\mu^Y} \right), \quad (15)$$

where we again dropped all terms irrelevant for a first-order approximation and have  $\kappa_Y = \frac{(1 - \lambda_Y)(1 - \lambda_Y \beta)}{\lambda_Y}$ . Here,  $\pi_t^F$  is the gross inflation rate of the average price of final goods,  $\pi_t^F := \frac{P_t^F}{P_{t-1}^F}$ , which, different from  $\pi_t$ , does not take into account whether a sector is locked down or not,  $mc_t := \frac{MC_t}{P_t}$  is the real marginal costs, and  $\mu^Y = \frac{\eta_F}{\eta_F - 1}$  is the target markup. The effective price  $P_t$ , the ideal price index, then exhibits an inflation rate  $\pi_t = \pi_t^F \left( \frac{\bar{H}_{t-1}}{\bar{H}_t} \right)^{\frac{1}{\eta_S - 1}}$ .

Importantly, the love-of-variety term  $\bar{H}_t^{\frac{1}{\eta_S - 1}}$  adds an element of as-if-perfectly-flexible prices to the model. In the first period in which the quarantine shock hits, some varieties are lost and  $\bar{H}_t$  falls. As a consequence, the effective price level jumps up even if all individual prices remain constant because households cannot perfectly substitute the lost varieties. As households expect the quarantine to be reduced in the future, they expect varieties to return and hence a falling effective price level from the love-of-variety component. This deflationary effect of the return of varieties to the consumption basket increases the real interest rate that households face and leads them to save more. This is the key mechanism behind the ‘‘Keynesian supply shocks’’ in Guerrieri et al. (2022), as they explain in Section 3.1 of their paper.

### 2.2.3 Intermediate Goods Producers

Intermediate goods are produced with a constant returns to scale production function, taking into account that a productivity weighted fraction  $H_t$  of labor and the fraction  $\bar{H}_t$  of capital is quarantined:

$$Y_t^F = (H_t N_t)^\alpha (\bar{H}_t u_t K_t)^{(1 - \alpha)}. \quad (16)$$

Here,  $u_t K_t$  is the effective capital stock taking into account utilization  $u_t$ , i.e., the intensity with which the existing capital stock is used. Using capital with an intensity higher than normal results in increased depreciation of capital according to  $\delta(u_t) = \delta_0 + \delta_1(u_t - 1) +$

$\delta_2/2(u_t - 1)^2$ , which, assuming  $\delta_1, \delta_2 > 0$ , is an increasing and convex function of utilization. Without loss of generality, capital utilization in the steady state is normalized to 1, so that  $\delta_0$  denotes the steady-state depreciation rate of capital goods.

Let  $mc_t$  be the relative price at which the intermediate good is sold to final goods producers. The intermediate goods producer maximizes profits,

$$mc_t Y_t^F - H_t w_t^F N_t - \bar{H}_t [r_t + q_t \delta(u_t)] K_t, \quad (17)$$

where  $r_t^F$  and  $q_t$  are the rental rate of firms and the (producer) price of capital goods, respectively. Only non-quarantined factors receive payments.<sup>10</sup> The intermediate goods producer operates in perfectly competitive markets, such that the real wage and the user costs of capital are given by the marginal products of labor and effective capital:

$$w_t^F = \alpha mc_t \left( \frac{u_t K_t \bar{H}_t}{N_t H_t} \right)^{1-\alpha}, \quad (18)$$

$$r_t^F + q_t \delta(u_t) = u_t (1 - \alpha) mc_t \left( \frac{N_t H_t}{u_t K_t \bar{H}_t} \right)^\alpha. \quad (19)$$

We assume that utilization is decided by the owners of the capital goods, taking the aggregate supply of capital services as given. The optimality condition for utilization is given by

$$q_t [\delta_1 + \delta_2(u_t - 1)] = (1 - \alpha) mc_t \left( \frac{N_t H_t}{u_t K_t \bar{H}_t} \right)^\alpha, \quad (20)$$

i.e., capital owners increase utilization until the marginal maintenance costs equal the marginal product of capital services.

Total production  $Y_t = \bar{H}_t^{\frac{1}{\eta_S - 1}} Y_t^F$  is scaled by an additional term  $\bar{H}_t^{\frac{1}{\eta_S - 1}}$ , which reflects the fact that the loss in varieties through the quarantine decreases the effective productivity of the economy even further.

#### 2.2.4 Capital Goods Producers

Capital goods producers take the relative price of capital goods,  $q_t$ , as given in deciding about their output, i.e., they maximize

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t I_t \left\{ q_t \left[ 1 - \frac{\phi}{2} \left( \log \frac{I_t}{I_{t-1}} \right)^2 \right] - 1 \right\}. \quad (21)$$

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<sup>10</sup>If the production unit is quarantined, quarantined capital is still depreciated at rate  $\delta_0 - \delta_1 + \delta_2/2$ . This means capital owners receive an average dividend payment on their capital  $r_t = r_t^F \bar{H}_t - (1 - \bar{H}_t) \delta(0)$ .

Optimality of the capital goods production requires (again dropping all terms irrelevant up to first order)

$$q_t \left[ 1 - \phi \log \frac{I_t}{I_{t-1}} \right] = 1 - \beta \mathbb{E}_t \left[ q_{t+1} \phi \log \left( \frac{I_{t+1}}{I_t} \right) \right], \quad (22)$$

and each capital goods producer will adjust its production until (22) is fulfilled.

Since all capital goods producers are symmetric, we obtain as the law of motion for aggregate capital

$$K_t - (1 - \delta(u_t)) K_{t-1} = \left[ 1 - \frac{\phi}{2} \left( \log \frac{I_t}{I_{t-1}} \right)^2 \right] I_t. \quad (23)$$

The functional form assumption implies that investment adjustment costs are minimized and equal to 0 in the steady state.

## 2.3 Government

The government operates a monetary and a fiscal authority. The monetary authority controls the nominal interest rate on liquid assets, while the fiscal authority issues government bonds to finance deficits and adjusts expenditures to stabilize debt in the long run.

We assume that in normal times monetary policy sets the nominal interest rate following a Taylor-type (1993) rule with interest rate smoothing:

$$\frac{R_{t+1}^b}{\bar{R}^b} = \left( \frac{R_t^b}{\bar{R}^b} \right)^{\rho_R} \left( \frac{\pi_t^F}{\bar{\pi}} \right)^{(1-\rho_R)\theta_\pi} \left( \frac{Y_t^F}{Y_{t-1}^F} \right)^{(1-\rho_R)\theta_Y}. \quad (24)$$

The coefficient  $\bar{R}^b \geq 0$  determines the nominal interest rate in the steady state. The coefficients  $\theta_\pi \geq 0$ ,  $\theta_Y \geq 0$  govern the extent to which the central bank attempts to stabilize inflation and output. We assume that the central bank reacts to average, i.e., measured, inflation,  $\pi_t^F$ , not effective price inflation,  $\pi_t$ , that depends on substitution elasticities for quarantined products and services. The parameter  $\rho_R \geq 0$  captures interest rate smoothing. For the first 21 months of the pandemic, March 2020 until December 2021, we assume that the central bank sets the interest rate to the zero-lower-bound and implement this via news shocks on the interest rate. Afterwards the interest rate reverts to the one implied by the Taylor rule.

The fiscal branch of the government follows a simple rule for spending that reacts only to the deviation of government debt from its long-run target in order to avoid fiscal dominance:



$$\frac{G_t}{\bar{G}} = \left( \frac{G_{t-1}}{\bar{G}} \right)^{\rho_G} \left( \frac{B_t}{\bar{B}} \right)^{(1-\rho_G)\gamma_B^G}, \quad (25)$$

where the coefficient  $\gamma_B^G$  determines the speed at which government debt is returned to its target level.

The government levies a constant tax rate  $\tau$  on labor income and profits so that total taxes  $T_t$  are given by  $T_t = \tau (w_t H_t N_t + \Pi_t^U + \Pi_t^F)$  and the government budget constraint determines government debt residually:

$$B_{t+1} = R_t^b / \pi_t B_t + G_t - T_t + \int \mathcal{T}_t(h_{it}) di + (1-\tau) \int_{e_{it} \neq \mathcal{E}} \mathcal{R}(h_{it}, e_{it})(h_{it} w_t N_t + \mathbb{I}_{h_{it} \neq 0} \Pi_t^U) di. \quad (26)$$

## 2.4 Goods, Bonds, Capital, and Labor Market Clearing

The labor market clears at the competitive wage given in (18). The bond market clears whenever the following equation holds:

$$B_{t+1} = B^d(R_t^b, p_{q,t}^{in}, r_t, q_t, \Pi_t^F, \Pi_t^U, w_t, \pi_t, \mathcal{T}_t, \Theta_t, \mathbb{E}_t V_{t+1}) := \mathbb{E}_t [\lambda b_{a,t}^* + (1-\lambda) b_{n,t}^*], \quad (27)$$

where  $b_{a,t}^*, b_{n,t}^*$  are functions of the states  $(b, k, h, e)$ , and depend on how households value asset holdings in the future,  $V_{t+1}(b, k, h, e)$ , and current “prices”  $(R_t^b, p_{q,t}^{in}, r_t, q_t, \Pi_t^F, \Pi_t^U, w_t, \pi_t, \mathcal{T}_t)$ . Future prices do not show up because we can express the value functions such that they summarize all relevant information on the expected future price paths. Expectations in the right-hand-side expression are taken w.r.t. the distribution  $\Theta_t(b, k, h, e)$ . Equilibrium requires the total *net* amount of bonds the household sector demands,  $B^d$ , to equal the supply of government bonds. In gross terms there are more liquid assets in circulation as some households borrow up to  $\underline{B}$ .

Last, the market for capital has to clear:

$$K_{t+1} = K^d(R_t^b, p_{q,t}^{in}, r_t, q_t, \Pi_t^F, \Pi_t^U, w_t, \pi_t, \mathcal{T}_t, \Theta_t, \mathbb{E}_t V_{t+1}) := \mathbb{E}_t [\lambda k_t^* + (1-\lambda)k], \quad (28)$$

where the first equation stems from competition in the production of capital goods, and the second equation defines the aggregate supply of funds from households—both those that trade capital,  $\lambda k_t^*$ , and those that do not,  $(1-\lambda)k$ . Again  $k_t^*$  is a function of the current prices and continuation values. The goods market then clears due to Walras’ law, whenever labor, bonds, and capital markets clear.

**Table 1:** External/calibrated parameters (monthly frequency)

Parameter	Value	Description	Parameter	Value	Description
<b>Households</b>			<b>Nominal frictions</b>		
$\beta$	0.99	Discount factor	$\kappa_Y$	0.009	Price rigidity
$\xi$	4.00	Relative risk aversion	$\kappa_w$	0.011	Wage rigidity
$\gamma$	2.00	Inverse Frisch elasticity	<b>Firms</b>		
$\lambda$	5.00%	Portfolio adj. prob.	$\alpha$	0.68	Share of labor
<b>Idiosyncratic Productivity</b>			$\delta_0$	0.58%	Depreciation rate
$\rho_h$	0.99	Persistence	$\eta_F$	11.00	Elasticity within sectors
$\sigma_h$	6.93%	Standard deviation	$\eta_S$	3.50	Elasticity between sectors
$\zeta$	0.02%	Trans. prob. W. $\rightarrow$ E.	$\eta_W$	11.00	Elasticity of substitution
$\iota$	2.37%	Trans. prob. E. $\rightarrow$ W.	<b>Monetary Policy</b>		
<b>Labor Market Transitions</b>			$\rho_R$	0.93	Inertia
$p_{q,ss}^{in}$	0.03%	Trans. prob. $\mathcal{E} \rightarrow \mathcal{Q}$	$\theta_\pi$	1.50	Inflation reaction
$p_q^{out,\mathcal{E}}$	25.00%	Trans. prob. $\mathcal{Q} \rightarrow \mathcal{E}$	$\theta_Y$	0.20	Output reaction
$p_q^{out,\mathcal{U}}$	8.33%	Trans. prob. $\mathcal{Q} \rightarrow \mathcal{U}$	<b>Fiscal Policy</b>		
$p_u^{in}$	1.20%	Trans. prob. $\mathcal{E} \rightarrow \mathcal{U}$	$\rho_G$	0.98	Inertia Spending
$p_u^{out}$	20.00%	Trans. prob. $\mathcal{U} \rightarrow \mathcal{E}$	$\gamma_B^G$	-0.75	Reaction Debt
<b>Q Process</b>			$\tau$	0.20	Tax rate level
$\rho_Q$	0.86	Autocorrelation	<b>Real frictions</b>		
$\Sigma_{Q,Y}$	0.04	Feedback activity $\rightarrow Q$	$\delta_s$	1.289	Capital utilization
			$\phi$	1.000	Investment adjustment

### 3 Parameterization

We solve the model by perturbation methods (Bayer and Luetticke, 2020; Bayer et al., 2020) and parameterize the model at *monthly* frequency in the following way. First, we calibrate or fix all parameters that determine the steady state of the model. Second, we specify the values of those parameters that govern the dynamics of the model in line with estimates from the literature.

Table 1 summarizes all parameter values. On the household side, we model the  $\mathcal{U}$ -state as regular unemployment. We target an unemployment rate of 6% and an average duration of 5 months in line with US data for the period 1980–2019, which yields  $p_u^{in} = 1.2\%$  and  $p_u^{out} = 20\%$ . The  $\mathcal{Q}$ -state, by contrast, is a rare state with probability mass in the steady state of almost zero ( $p_{q,ss}^{in} = 0.03\%$ ). In both states, households receive government transfers that replace 25% of their after-tax labor income capped at 50% of median income.<sup>11</sup> Households in the  $\mathcal{Q}$ -state receive an additional \$2,400 per month. The exit probability from the  $\mathcal{Q}$ -state is 33.33% per month ( $p_q^{out,\mathcal{E}} + p_q^{out,\mathcal{U}} = 1/3$ ) so that the expected lockdown duration

<sup>11</sup>Here we assume an average of the stipulated replacement rate (40%) and the worst case replacement rate (10%) computed by Krueger et al. (2016). This number takes into account that the eligibility, up-take, and duration of unemployment benefits is limited.

is 3 months. When exiting the  $\mathcal{Q}$ -state, there is a 75%-chance of directly being employed. In our experiments in the next section, the aggregate  $\mathcal{Q}$ -shock increases  $p_{q,t}^{in}$ , the probability of entering the  $\mathcal{Q}$ -state. As explained, we allow the probability of entering the  $\mathcal{Q}$ -state to depend on labor productivity. In particular, we match the incidence of job losses across the income distribution during March/April 2020 as documented in Mongey et al. (2021).<sup>12</sup> For that purpose, we assume that the likelihood of entering the  $\mathcal{Q}$ -state is described by a logistic function in labor income, where the probability for the 25th percentile of the income distribution is three times higher than for the 75th percentile. The parameters of Process (2) are set to  $\rho_Q = 0.86$  and  $\Sigma_{Q,Y} = 0.04$  in order to match aggregate unemployment dynamics, as discussed in more detail in Section 4.1 below.

We take estimates for idiosyncratic income risk (after tax and transfers) from Storesletten et al. (2004), assuming  $\rho_h = 0.993$  and  $\bar{\sigma}_h = 0.069$ . Guvenen et al. (2014) provide the probability that a household will fall out of the top 1% of the income distribution in a given year, which we take as the transition probability from entrepreneur to worker,  $\iota = 2.37\%$ .

We set the relative risk aversion to 4, which is common in the incomplete markets literature; see Kaplan and Violante (2014). We set the Frisch elasticity to 0.5; see Chetty et al. (2011). For the calibration of the remaining household parameters, we match 4 targets: 1) average illiquid assets ( $K/Y=286\%$  annual), 2) average liquidity ( $B/Y=47\%$  annual), 3) the fraction of borrowers, 16%, and 4) the average top 10% share of wealth, which is 67%. This yields a monthly discount factor of 0.991, a monthly portfolio adjustment probability of 5.0%, a borrowing limit of two average monthly incomes, and a transition probability from worker to entrepreneur of 0.02%.<sup>13</sup>

For the firm side, we set the elasticity of substitution between differentiated goods within a sector to 11, which yields a markup of 10%. The labor share in production,  $\alpha$ , is 68%, implying a labor income share of 62%, given the 10% markup. The elasticity of substitution between labor varieties is also set to 11, yielding a wage markup of 10%, which is, however, redistributed to workers, leaving the labor income share unchanged. The depreciation rate is 0.58% per month. All these are standard values in the literature. We set the elasticity of substitution across sectors to 3.5, somewhat below the intertemporal elasticity of substitution. This ensures that the  $\mathcal{Q}$ -shock shares the features of a “Keynesian supply shock” as put forward by Guerrieri et al. (2022), in addition to raising the income risk of households.

The government taxes labor and profit income. The level of taxes in the steady state,  $\tau$ , is set to clear the government budget constraint at a level of government spending that

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<sup>12</sup>Specifically, they find that below median labor income workers are three times more likely to become unemployed (see their Figure 5B).

<sup>13</sup>Detailed data descriptions and sources can be found in Appendix A.

amounts to 15% of output. As we have assumed indexation to the steady-state inflation rate in the Phillips curves, we set the steady-state inflation rate w.l.o.g. to zero. The steady-state net interest rate is set to 0.0%, too, in order to capture the average federal funds rate in real terms minus output growth.

The Taylor rule coefficients on inflation, 1.5, output growth, 0.2, and interest rate inertia, 0.93 at a monthly level, are in line with the literature. The fiscal rule that governs spending is parameterized to ensure that public debt is slowly brought back to the steady state after a debt build-up. The parameters that govern the real and nominal frictions are set to the values estimated via Bayesian methods by Bayer et al. (2020). The parameter values for nominal frictions are in line with the representative-agent literature, with price and wage stickiness being less than 12 months on average.

## 4 Results

Having set up and calibrated the model, we use it to quantify the effects of the CARES transfers. In a first step, we develop our baseline scenario for which we expose the model economy to the quarantine shock, or “Q-shock” for short. We specify the shock in such a way that the model predictions match the actual developments of the unemployment rate during 2020/21 because the exceptionally strong rise of U.S. unemployment is one of the defining features of the COVID-19 recession. Next, we benchmark the predictions of the model for other variables against actual developments and find the model performs rather well.

To assess the effect of the Coronavirus stimulus—which is put in place under the baseline scenario—we study a counterfactual where the stimulus is switched off. For the entire package, we find a transfer multiplier of about 0.5. As we explore systematically the determinants of the multiplier, we identify a number of important aspects. In particular, the multiplier of the conditional transfer, that is, the Federal Pandemic Unemployment Compensation (FPUC), exceeds 1 when it comes online because it limits the idiosyncratic income risk triggered by the Q-shock. Finally, we also look at the distributional and welfare consequences of the Q-shock and the CARES package. Here, we find that the shock itself has significant welfare costs, especially for those households that lack financial resources to self insure, and the CARES package is well able to eliminate these negative welfare consequences.

### 4.1 The Q-shock

In our model, the COVID-19 recession is caused by the Q-shock: it causes a reduction of the level of economic activity—either voluntary to avoid infection risk or mandated via

lockdowns—and applies to workers, capital, and final-goods sectors alike. While the  $Q$ -shock causes exogenously a reduction of activity, the model allows for feedback from economic activity to the state of the pandemic. In the model, we capture such feedback via a stylized rule and omit microfoundations developed elsewhere (see, e.g., Eichenbaum et al., 2021).

While under quarantine, final goods are temporarily unavailable for consumption; capital and workers, in turn, do not receive market income. Workers that lose their income and job because of the  $Q$ -shock qualify for FPUC which provides, on top of regular unemployment benefits to which an individual is entitled to under state laws, a \$600 benefit for each week of unemployment between April 5, 2020 and July 31, 2020. After July 2020, a number of additional assistance measures were put in place, but they were only available for a limited time and we abstract from those payments in order to measure the effect of the transfers under the CARES act as initially specified.

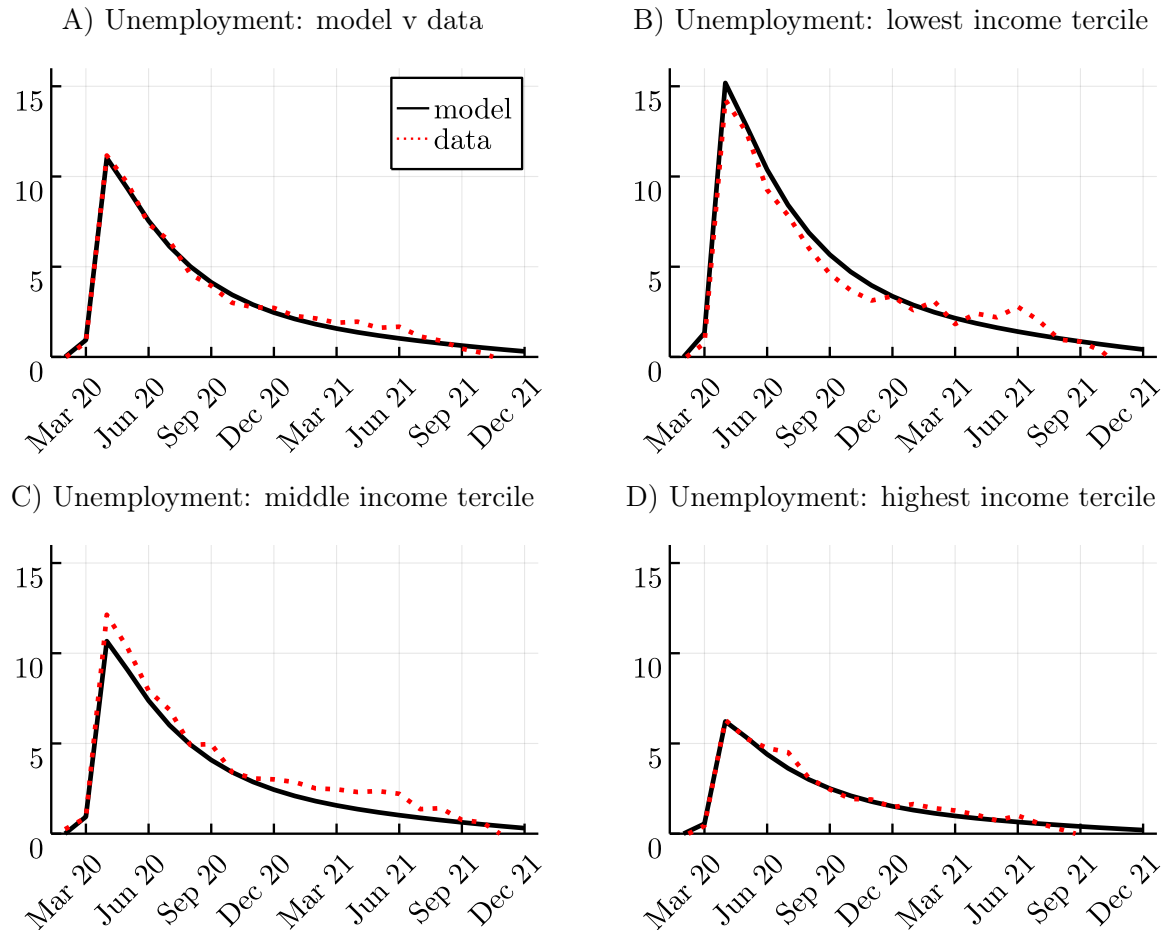
To determine the size and the persistence of the  $Q$ -shock as well as the endogenous feedback from the economy to the state of the pandemic determined by Equation (2) above, we target the actual time path of the unemployment rate. As a result, the total amount of FPUC payments in the model sums to \$274 billion during 2020, which is very close to the actual amount of \$265 billion.<sup>14</sup> Specifically, we assume innovations to the  $Q$ -shock process in March, April and May 2020 such that the average quarantine risk amounts to 1, 11, and 3 percent, respectively. Thereafter, there are no further innovations to the  $Q$ -process.<sup>15</sup> The sequence of innovations to the  $Q$ -shock process becomes fully known in February (“period 1”), that is, innovations are modelled as “news shocks.” As a result, the future path of the *probability* to enter the  $Q$ -state is fully known and there is no *aggregate* risk. However, income risk at the individual level is very high because it is unclear which worker will end up in the  $Q$ -state. That said, we stress that our baseline is still conservative because the 3 percent quarantine risk for May is considerably below what would be observed without the anticipated innovation for May. In a series of robustness checks on the information structure, we first consider a variant with incomplete anticipation such that households expect in March a much higher income risk in May and are positively surprised in April. Second, we consider an alternative that features an anticipated second wave of quarantines in late 2020.

Given the parameterization detailed in Section 3 above, we pick the parameter values which govern the endogenous feedback from aggregate activity to the  $Q_t$  process,  $\Sigma_{Q,Y}$ , and

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<sup>14</sup>Measured as total outlays documented by the Bureau of Economic Analysis in the personal income statistics under Pandemic Unemployment Compensation Payments. See also our Data Appendix A.

<sup>15</sup>Since the FPUC payments are tied to unemployment caused by the  $Q$ -shock, our analysis assumes that FPUC payments start already in March (rather than in April). Yet the payouts in March are very small. Assuming instead that the newly unemployed in March receive regular unemployment benefits does not alter our results below in a material way.



**Figure 2:** Unemployment rate. Notes: unemployment rate is measured in percentage-point detrended deviation from February-2020 level; black solid line is model prediction, red dotted line represents data.

its autocorrelation,  $\rho_Q$ , to target the sharp decline in unemployment rates between May and September 2020 and the relatively flat tail between September 2020 and September 2021. Note that our parameterization also implies that workers in the  $Q$ -state have a seven times higher likelihood to become regular unemployed than employed workers have (in the  $\mathcal{E}$ -state).

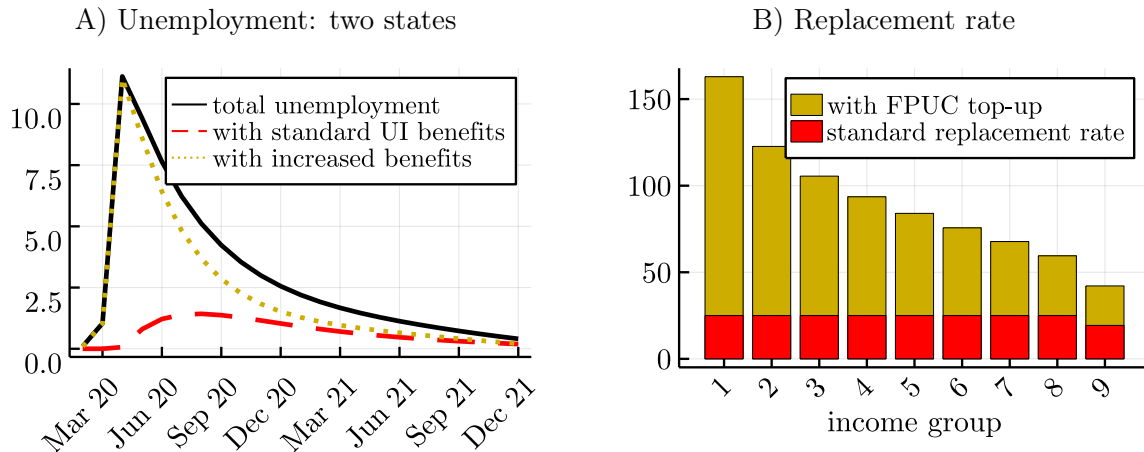
Besides the FPUC payments that are linked in our model to the  $Q$ -state, the CARES Act also established another transfer: a one-time payment of \$1,200 to everybody, except for households in the top 10% of the income distribution. This is a minor form of conditionality and we capture this in the model by linking it to productivity  $h$ . Still, in what follows, we refer to it, to highlight the difference to the FPUC payments, as “unconditional transfers”. In the simulations, we assume that, as of March 2020, these payments are known to arrive in April. The total transfer to an entitled person amounts to \$1,200 and \$283 billion in total. In the aggregate, the two transfer components are thus of approximately the same size.

By construction, the model captures the actual development of the unemployment rate during the COVID-19 recession, as Panel A) of Figure 2 illustrates. Here, and in what follows, the horizontal axis measures time at monthly frequency from February 2020 to December 2021. The predictions of the model are shown by the black solid line and compared to the data in shown by the red dotted line. The vertical axis measures the deviation (in percentage points) from the pre-shock level observed in February 2020. Total unemployment peaks in April at 11 percentage points (above its February level) and declines afterwards. In the other panels of the same figure, we zoom in on the evolution of income-tercile-specific unemployment rates as predicted by the model and contrast it with the actual developments of the unemployment rate for three distinct education groups: no high-school or high-school graduates w/o college or less (Panel B), some college (Panel C), and Bachelor degree (Panel D), as reported in the FRED database maintained at the St. Louis Fed. Each of the three groups represents roughly one third of the labor force. It turns out that the model predictions for the incidence of unemployment across the three terciles captures the actual developments for the three education groups rather well. A key aspect of these developments is that the incidence of the unemployment rate is considerably higher in the low-income group (Panel B). Here the unemployment rate peaks some 15 percentage points above its pre-shock level. For the high-income group (Panel D), the peak is at about 6 percentage points only. This is consistent with evidence reported by Mongey et al. (2021) and Cortes and Forsythe (2021) which shows that low-education and low-income occupations were indeed disproportionately exposed to the pandemic shock.

In Figure 3, Panel A), we decompose the increase of the total unemployment rate into the underlying states. Initially, all additional unemployed are in the  $\mathcal{Q}$ -state (golden dotted line) and hence receive FPUC in addition to regular unemployment benefits. Over time, as more and more workers exit the  $\mathcal{Q}$ -state, the number of workers in regular unemployment increases, but the increase remains moderate compared to the initial jump of the unemployment rate. As a result, about two-thirds of the FPUC is paid out in the period up to July 2020.<sup>16</sup> Because the FPUC payments are relatively large and do not vary with income, they imply replacement rates that are falling in income. This is shown in Panel B) of Figure 3. The replacement rate for regular unemployment benefits is shown in red and the one implied by the FPUC in gold, for each of the nine equally large income groups which we track in the state-space of the model (roughly deciles of the income distribution). For regular unemployment benefits our model calibration implies a replacement rate of 25%, and homogeneously across the

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<sup>16</sup>As detailed in Section 3, our simulation assumes a smooth transition from the  $\mathcal{Q}$ -state to regular unemployment. This is a computationally efficient way to approximate the discrete termination of the FPUC payments in July 2020. It also captures the initial uncertainty about the termination of the FPUC scheme because it renders the duration of FPUC payments stochastic from an individual worker’s perspective.



**Figure 3:** Unemployment states and replacement rates. Notes: Panel A shows composition of total unemployed (black solid) into those with FPUC (golden dotted line) and those with only regular unemployment benefits (red dashed line). Panel B shows replacement rates across income states, both in the regular  $\mathcal{U}$ -state (red) and the top-up in  $\mathcal{Q}$ -state (gold).

income distribution. Accounting for FPUC, raises the replacement rate to more than 150% at the bottom of the income distribution. It also raises it at the top but much less so. That replacement rates for the unemployed exceeded 100% because of the FPUC has been widely discussed (Ganong et al., 2020). In fact, as we show below, this feature of the CARES package adds to its effectiveness in terms of stabilizing economic activity.

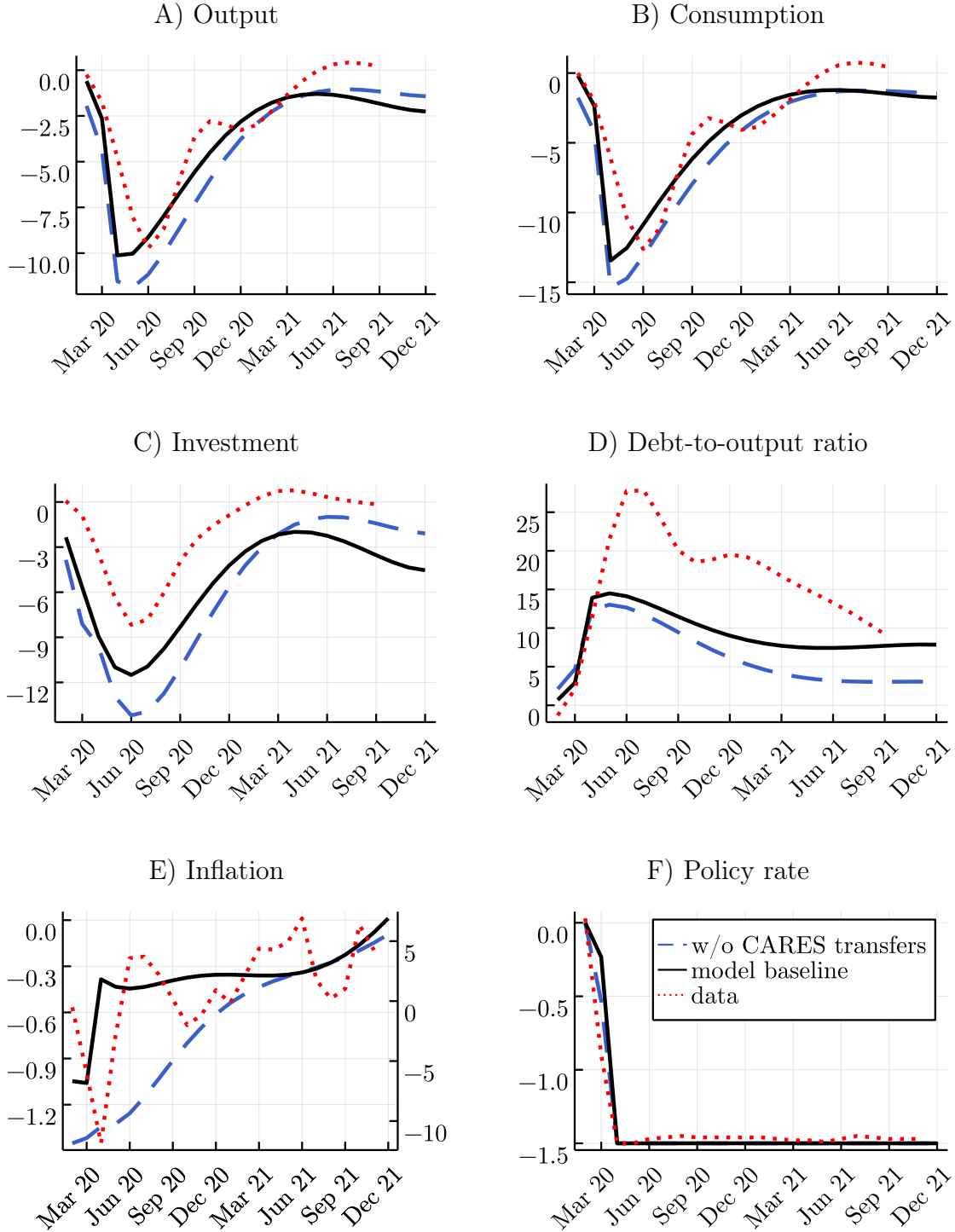
## 4.2 The COVID-19 recession

We have specified the Q-shock such that model prediction for the unemployment rate aligns well with actual developments. We now turn to the model predictions for the broader macroeconomic impact of the Q-shock, comparing predictions for the behavior of selected variables to their empirical counterparts. For this purpose, we remove (when necessary) an HP-trend from the actual time series data and consider the developments from February 2020 to December 2021, relative to the pre-shock period.<sup>17</sup> In our discussion, we abstract from the effects of other shocks, assuming effectively that the macroeconomic developments during 2020/21 have been dominated by the pandemic. The red dotted line in Figure 4 shows the data, the black solid line the model prediction under the baseline which—importantly—features the CARES transfers payments as discussed in the previous section.

Panel A) shows the adjustment of output which contracts sharply: Relative to the pre-COVID level, output declines by 10 percent. Here the prediction of the model is right on

<sup>17</sup>Quarterly series are transformed to monthly frequency via cubic spline interpolation, c.f. Appendix A.





**Figure 4:** Impulse responses to Q-shock. Notes: for details on data see Appendix A. Output, consumption, and investment are deflated with the actual price index  $P_t^F$  rather than the ideal price index  $P_t$ . Panel E) depicts annualized month-on-month inflation rate (based on  $P_t^F$ ), measured against the left axis (model) and against the right axis (right). Y-axis: Percentage deviation from steady state, annualized percentage points in case of (m-o-m) inflation and interest rate. X-axis: Months.

track: the maximum effect is very similar and takes place only a little bit earlier compared to the data (cf the black solid and the red dotted lines). The recovery of economic activity predicted by the model is also very similar to the actual developments, even though it is a little bit slower towards the end of the period under consideration. We show the adjustment of consumption and investment in Panels B) and C) of the same figure. Again we observe that the predictions of the model align quite well with actual developments, although the model overpredicts the drop in investment somewhat. In any case, it bears noting that the contraction of consumption is stronger than the response of investment, both according to the data and the model. This pattern sets the COVID-19 recession apart from more conventional business cycles. Panel D) shows the response of public debt, measured in percent of current output (and relative to the January level). It increases sharply, but less so in the model than in the data. This is unsurprising because the CARES package also features a number of additional expenditure items which we do not consider in our analysis. Towards the end of the period under consideration, the actual debt-to-output ratio declines rather swiftly because output rebounds. Nevertheless, the pandemic and the CARES package leave their mark on public debt for an extended period.

The developments of inflation are shown in the bottom-left panel of Figure 4. Here, the model predictions fail to capture the actual dynamics observed during 2020/21 from a quantitative point of view.<sup>18</sup> For this reason, we measure the model predictions against the left axis and the data against the right axis. Initially, the monthly inflation rate drops sharply in the data by some 10 percentage points (annualized). This drop of inflation is often taken as evidence that the pandemic—while apparently a supply shock—induced substantial demand shortages, too (for instance, Fornaro and Wolf, 2020; Baqaee and Farhi, 2021). Yet, it turns out, that capturing the impact of the pandemic on inflation is both conceptually and quantitatively challenging, even in models which allow for the pandemic to operate via a demand contraction (Guerrieri et al., 2022; Dietrich et al., 2022). Against this background it is noteworthy that our model predicts the inflation developments fairly well—at least from a qualitative point of view. It predicts a strong drop of inflation in March 2020, followed by a gradual recovery over time. This is because in the model there is initially a contraction of both supply and demand. First and foremost, the Q-shock reduces the effective labor force and the effective capital stock in the economy and thus lowers its productive capacity. But the same shock—and this is the focus of our analysis below—also adversely impacts aggregate demand, through the love-of-variety effect due to Guerrieri

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<sup>18</sup>According to widely held beliefs, actual inflation dynamics are to a considerable extent driven by fluctuations in commodity prices, also in the context of the pandemic (see, for instance, Budianto et al., 2021). We do not consider these in our model.

et al. (2022), but notably also as it increases idiosyncratic income risk. Households try to self-insure against this risk by increasing their liquid savings.<sup>19</sup> This, in turn, generates a reduction of demand, as apparent from the consumption response shown in Panel B).

Lastly, in Panel F) we show the response of the policy rate. In line with actual developments, the model assumes a reduction of the policy rate by 1.5 percentage points in March 2020. This brings the policy rate to its lower bound which constrains monetary policy throughout the period under consideration.<sup>20</sup>

Overall, we find that the model predictions under the baseline align rather well with actual developments during 2020/21 with the exception of inflation. The alternative version of the model where the  $Q$ -shock is not fully anticipated predicts a much larger drop in inflation early in the COVID-19 recession (see Figure A.2 in Appendix B), suggesting that expectations have been excessively negative at the onset of the pandemic. Still, for the baseline we opt for the conservative scenario. All other aggregate dynamics are very similar in the two information treatments.

Against this background, we can determine the macroeconomic impact of the transfers under the CARES package through a counterfactual. Specifically, we simulate the model response to the same  $Q$ -shock as above, but assume—counterfactually—that workers in the  $Q$ -state do not receive any additional unemployment benefit beyond the level which they receive in the regular unemployment state. In other words, there are no FPUC payments in the counterfactual and neither is there an unconditional transfer. The model prediction for this counterfactual scenario appear as the blue dashed lines in Figure 4. Comparing them to the baseline (black solid) lines allows us to quantify how the Coronavirus stimulus contributed to the economic adjustment to the pandemic.

We find that absent the stimulus, the collapse of economic activity at its trough would have been almost 2 percentage points larger. And the recovery during the second half of 2020 would have been markedly slower such that the cumulative output loss would have been larger by about 13 percent (of monthly GDP). This is because—absent the CARES transfers—the economy would have suffered from a stronger contraction of consumption.<sup>21</sup> Investment, too, would have declined more strongly. Perhaps unsurprisingly, the debt-to-output ratio would

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<sup>19</sup>In terms of aggregate dynamics this looks like a “risk premium shock,” a driving force of business cycles in standard macro models (see, for instance, Smets and Wouters, 2007).

<sup>20</sup>Concretely, we feed into the model a series of news about monetary policy such that households correctly expect the policy rate to be at the effective lower bound from April 2020 to December 2021. This is also in line with the 2020 FOMC projections for the Federal Funds Rate. After 2021, we assume that the policy rate follows the Taylor rule again.

<sup>21</sup>Cox et al. (2020) provide evidence in support of our results. They use household-level bank data and document that, after an initial drop, spending has rebounded most rapidly for low-income households since mid-April 2020. According to the authors this suggests that the CARES stimulus program played an important role in limiting the effects of labor market disruptions on spending.

have increased somewhat less strongly.<sup>22</sup> And while we do not observe a material difference in the response of monetary policy in Panel F), there is a noticeable difference between the counterfactual and the baseline in Panel E): Inflation declines considerably more strongly in the counterfactual. This, in turn, illustrates that transfer payments contribute to stabilizing aggregate demand, in particular by providing insurance—a key aspect which we discuss in more detail in the next section.

### 4.3 The Transfer Multiplier

We finally turn to the question that motivates our analysis: How large is the transfer multiplier? To answer this question, it is important to distinguish transfers which are paid to the unemployed (via the FPUC) and the—by and large—unconditional transfer payments which have also been part of the CARES package. Panel A) in Figure 5 displays the transfer multipliers for our baseline specification. Here, we measure time, as before, in months along the horizontal axis and the cumulative multiplier along the vertical axis: the cumulative output change in all periods up to horizon  $k$  that is due to the transfer, divided by the cumulative transfer payments up to the same horizon (see, for instance, Ramey, 2019). In the figure, we show the cumulative transfer multiplier from period 3 onward. This corresponds to April 2020 in our analysis when sizeable FPUC payments are starting to come online. Before April, hardly any (no) transfers are being paid out in the model (in the data).

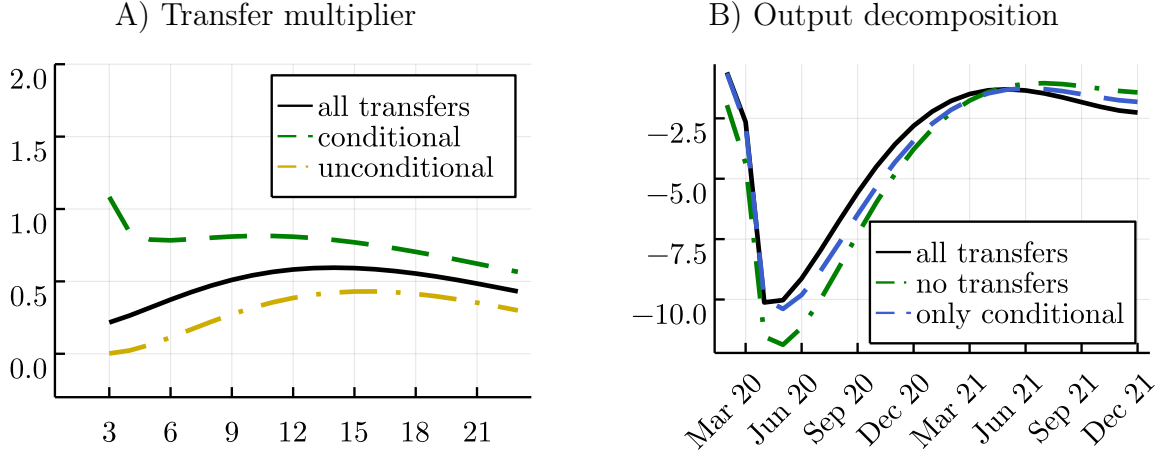
The black solid line shows the multiplier for the total transfers to households provided for by the CARES Act. Initially, that is, in period 3 (April 2020), the cumulative multiplier is small, a finding familiar from earlier model-based analyses (Coenen et al., 2012; McKay and Reis, 2016; Giambattista and Pennings, 2017).<sup>23</sup> To shed more light on our result, we decompose the multiplier: the green dashed line and the golden dashed-dotted line in Panel A) represent the multiplier for the conditional and the unconditional transfer under the CARES Act. Here we obtain values of close to unity and basically zero, respectively. The overall multiplier is an average of the two weighted with cumulative payments.

The difference is rather stark and two aspects are key for this. First, the conditional transfer is directed to the unemployed who have a high marginal propensity to consume. Importantly, this matters already before the transfer is paid out. As shown by Auclert et al.

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<sup>22</sup>Erceg and Lindé (2014) identify conditions under which fiscal stimulus may lower the debt-to-output ratio, notably in the context of the zero lower bound. Similarly, there is evidence that contractionary fiscal policy measures can at times raise the debt-to-output ratio (Born et al., 2020). We abstract from the possibility that the economic fallout from the COVID-19 pandemic impairs fiscal sustainability, since it is arguably less of an issue in the U.S. Hürtgen (2021) analyzes fiscal sustainability during the COVID-19 pandemic for selected euro-area countries.

<sup>23</sup>Recent time-series studies obtain larger estimates (Gechert et al., 2021).

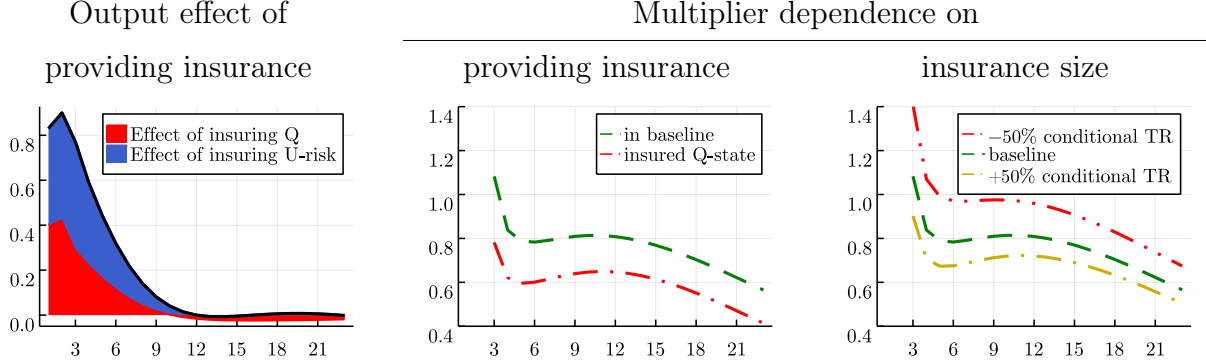


**Figure 5:** Output effect of transfers. Notes: Panel A) shows cumulative multiplier computed as  $\sum_{j=1}^k y_i / \sum_{j=1}^k t_i$ , where  $y_i$  is the deviation of output from baseline,  $t_i$  is the transfer payment (both measured in percentage points of steady-state output), and  $k$  is the time since announcement in period 1 (February 2020), measured along the horizontal axis, shown for period  $k = 3$  onward. Panel B) shows output responses for baseline (black solid) and alternative specifications with conditional transfers only (blue dashed) and w/o transfers (green dash-dotted). Y-axis: cumulative multiplier (right panel), percentage deviation from steady state (left panel). X-axis: Months.

(2018), in HANK models such as ours, anticipated income changes impact current spending via the “intertemporal marginal propensity to consume”: households that operate near their liquidity constraint may raise expenditures in response to an expected increase in income in the near future.<sup>24</sup> Second, the conditional transfer boosts aggregate demand because it reduces income risk. This happens even though transfers have not yet materialized. For these reasons the multiplier of the conditional transfer tends to be very large in period 1 and 2. We do not show it in the panel so as not to distort the picture. Over time the cumulative multiplier of conditional transfers declines as income risk is receding and conditional payments are materializing. Instead, the unconditional transfer multiplier increases somewhat in the medium run. As a result, cumulative multipliers become more aligned for longer horizons. For a one-year horizon we obtain values of about 0.8 and 0.4, respectively.

In Panel B) of Figure 5 we decompose the effect of the CARES transfers on output by contrasting the baseline response which features both transfer components (in black) to the output response for two alternative model specifications: one w/o transfers at all (green dashed-dotted line) and one where only the conditional transfers are being paid (blue

<sup>24</sup>This effect is absent in TANK models since there the borrowing constraint of non-optimizing households is always binding.



**Figure 6:** Insurance Effects. Notes: left panel decomposes output effect the of the conditional transfer into contributions due to insuring idiosyncratic income risk in  $Q$ -state (red) and providing funds for self-insurance against income drop in  $U$ -state (blue). Center and right panels show transfer multiplier of the conditional transfer in the baseline model (dashed green) and (center panel) alternative model w/o idiosyncratic income risk in  $Q$ -state (red dashed dotted), as well as (right panel) for alternatively sized transfer packages (red dashed dot-dotted and gold dashed dotted). Y-axis: percentage points (left), cumulative multipliers (right). X-axis: months after start of stimulus.

dashed line). The figure shows that the conditional transfer payment is making almost all the difference (for in this case the response is almost the same as in the baseline). This is consistent with the results for the multiplier shown Panel A) of the same figure but still noteworthy because the overall amount of payments are about the same for both transfer types (in the model: \$274 billion (conditional) vs. \$283 billion (unconditional)).

The conditional transfer is more effective in stabilizing the economy for three reasons. First, it insures the income risk associated with the  $Q$ -state itself. Second, because it overinsures—via the exceptionally large replacement rates—the  $Q$ -state, the conditional transfer provides additional resources to those households that transition into the  $U$ -state after their quarantine ends. Third, because low income households are more likely to end up in the  $Q$ -state, it redistributes to low-income, high-MPC households.

We illustrate these three channels in Figure 6. For the purpose of this figure, we solve an alternative model where income of  $Q$ - and  $\mathcal{E}$ -workers is pooled conditional on their productivity. Therefore, in this version of the model, the direct effect of  $Q$ -state income risk is eliminated. The increase of  $U$ -unemployment risk after quarantine, however, remains. What also remains, just as in the baseline, is that on average low-productivity workers receive more FPUC transfers than high-productivity workers. The transfers are just pooled across the  $Q$ - and  $\mathcal{E}$ -workers.

The left panel of Figure 6 shows how the insurance effects play out in terms of stabilizing

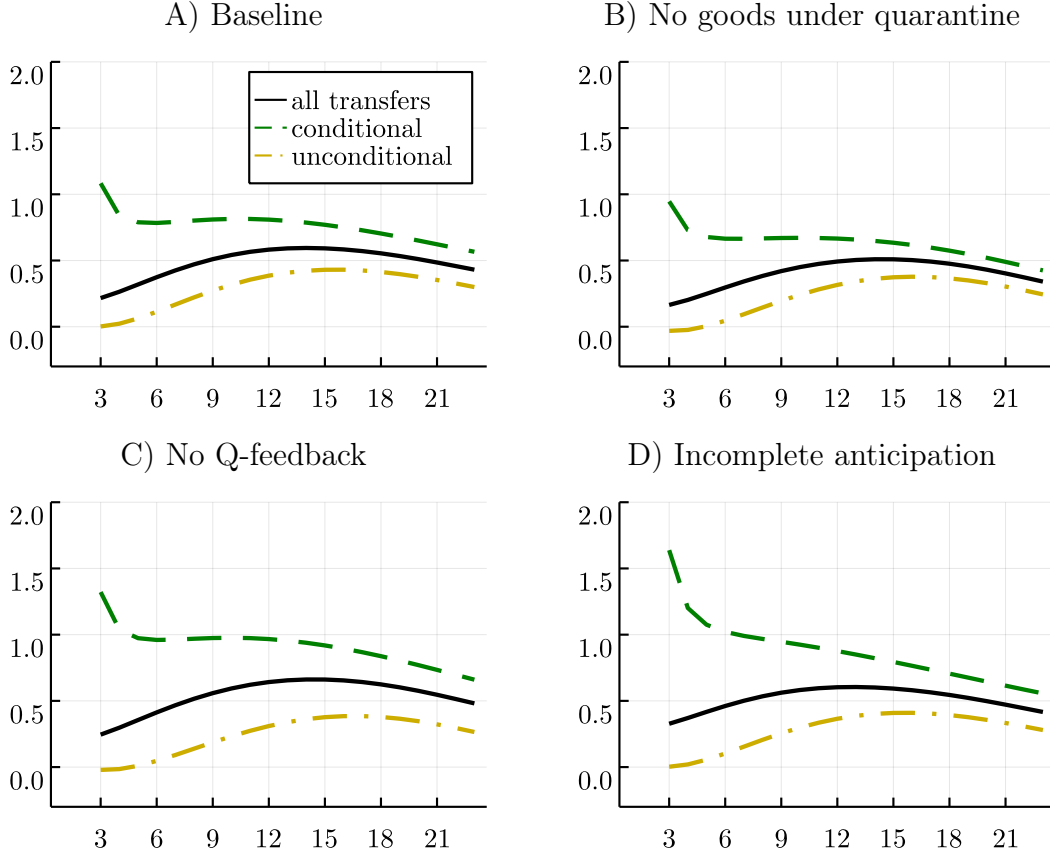
output. In red, it shows by how much output in the alternative model exceeds output in the baseline as a result of the income risk associated with the  $\mathcal{Q}$ -state being fully insured. Recall that there are no FPUC payments, so that the full  $\mathcal{Q}$ -risk effect operates in the baseline model. And in the absence of this effect output falls less. On top of this, in blue, the figure shows how much greater the stabilizing effect of FPUC payments is in the baseline model compared to the alternative with income pooling. This greater stabilization results from FPUC payments being targeted to quarantined households which use them to self-insure against the income risk associated with the regular  $\mathcal{U}$ -state. Because workers in the  $\mathcal{E}$ -state anticipate this their desire for precautionary saving is lower and aggregate demand higher. The total effect of both insurance effects is close to 1 percent of output at peak.

This insurance channel also shows itself in terms of multipliers in the center panel of Figure 6. The green dashed line is the transfer multiplier for the FPUC payments in our baseline model. When income is pooled in the  $\mathcal{Q}$ -state (red dash-dotted line), the multiplier is significantly smaller because both the  $\mathcal{Q}$ -risk itself is insured and the FPUC payments are no longer targeted to high  $\mathcal{U}$ -risk households. However, the transfer multiplier of the FPUC payments is still larger than the unconditional transfer multiplier because of the targeting to low-income, high MPC households.

Furthermore, the right panel of Figure 6 shows that there are decreasing returns to providing additional insurance. Had the FPUC payments been half the size of the actual payments, the resulting multiplier would have been more than 20% larger (see red dash-dot-dot line). In absolute terms, this means that the effect of the first half of the FPUC payments (\$137 billion) on GDP is thus \$30 billion larger than the effect of the second half. Similarly, a further increase of FPUC payments (gold dash-dot line) would have decreased the multiplier.

Finally, we assess the role of three other pandemic-related model features for our results. For this purpose, Figure 7 compares the transfer multipliers of the baseline model (top-left panel) to a variant where no goods are quarantined and, hence, the love-of-variety effect à la Guerrieri et al. (2022) is absent (top-right panel), to a variant without feedback from aggregate activity to quarantine (bottom-left panel), and to a variant where the full path of the  $\mathcal{Q}$ -shocks is not known in February, but only learned by April (bottom-right panel).

Eliminating the love-of-variety effect virtually leaves the transfer multipliers unchanged, even though it has a first-order effect on aggregate dynamics (which we illustrate in Figure A.2 in Appendix B). In contrast, removing the activity-quarantine feedback increases the multipliers substantially, in particular so during the first months. This illustrates a potential caveat of economic stimulus in a pandemic: some of its impact is lost to the extent that increased economic activity induces the state of the pandemic to worsen which, in turn,

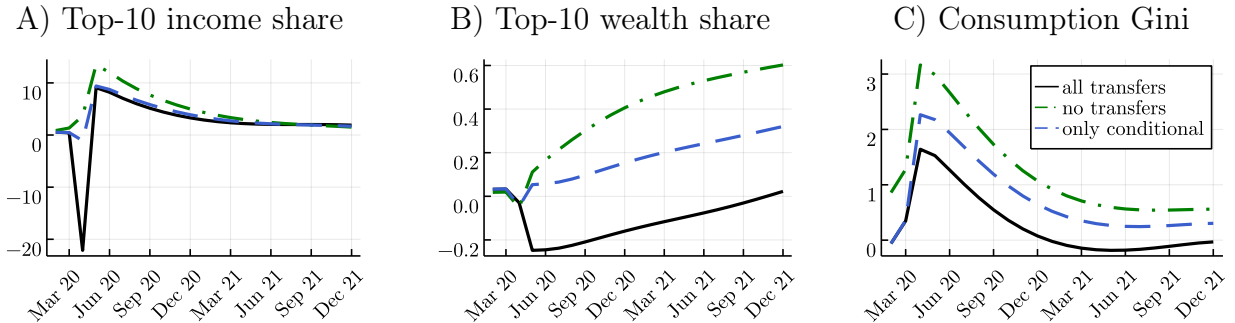


**Figure 7:** Multiplier dependence on Q-shock features. Notes: top-left panel replicates the baseline multipliers. Top-right panel shows multipliers when no goods are in quarantine. Bottom-left panel shows multipliers without feedback from aggregate activity to quarantines. Bottom-right panel shows multipliers when Q-shocks in March and April 2020 are not anticipated. X-axis: months after start of pandemic.

necessitates further quarantine measures.

Considering Panel D), we observe that learning about the Q-shock sequence only gradually (incomplete anticipation) increases the multipliers. This is because given the overall persistence of the Q-shock, the new “quarantines” in May turn out lower than expected. In the baseline, this benign outcome is revealed already in February 2020, while, in the alternative, households expect a much bleaker situation with higher income risks. In this scenario, the conditional transfer turns out to be an even stronger instrument to stabilize economic activity. The multiplier of the unconditional transfer, instead, remains basically unchanged relative to the baseline. In Appendix C we also show that the multiplier is not affected by waves in product quarantines and, similar to the incomplete anticipation case, increases somewhat if households expect an additional wave of quarantine risks in late 2020.



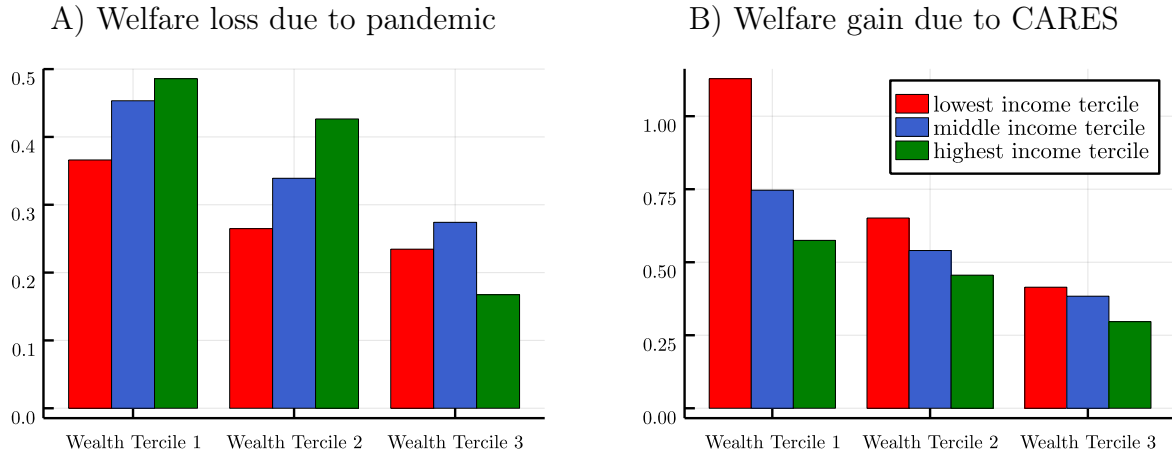


**Figure 8:** Distributional effects of CARES transfer payments. Notes: Black solid line shows baseline response w/ both conditional and unconditional transfers, green dash-dotted line without CARES transfers, and blue dashed line w/ conditional transfer only. Y-axis: Percentage deviation from steady state. X-axis: Months.

#### 4.4 Distributional Effects and Normative Implications

Our model captures key aspects of the pandemic recession fairly well in terms of both its macroeconomic impact and its heterogeneous impact at the household level. The incidence of unemployment, for instance, differs strongly across the income distribution as does the replacement rate, as Figures 2 and 3 above illustrate. In what follows we highlight further distributional aspects of the pandemic which are widely debated (e.g. Adams et al., 2020; Chetty et al., 2020; Han et al., 2020; Hanspal et al., 2021). Afterwards, we compute the welfare effects of both the Q-shock and the Coronavirus stimulus.

Figure 8 shows the response of various inequality indicators to the Q-shock. In each instance, we compare the baseline with all transfers in place (black solid line) to a counterfactual without unconditional transfers (blue dashed line) and with no transfers at all (green dash-dotted line). Panel A) on the left shows the response of the top-10% income share. According to this measure, the pandemic leads to an increase in income inequality (except initially, that is in April 2020), even with transfer payments, and this increase is, with almost 10 percent, economically significant. At the same time, we observe that the transfer payments dampen the impact on income inequality: it would have risen even more in their absence. This finding is also supported by Panel B) which shows the top-10% wealth share. Here we see a decline in inequality in the baseline, an effect which would not have been observed without transfers. The stronger increase in government debt that finances transfers, together with the redistributive character of the transfers themselves, leads to an increase in the real rate on liquid assets and, thereby, fosters wealth accumulation of the relatively poor along the lines explained in Bayer et al. (2021). This effect is quantitatively small, however. Finally, consumption inequality measured by the Gini and shown in Panel C) still rises in all scenarios but again the transfers dampen the increase, and quite strongly



**Figure 9:** Welfare effects of pandemic and CARES transfer payments. Notes: The welfare gains are group averages of consumption equivalents (in percentage points). N.B. the numbers include the indirect effects on future government spending which is assumed to be pure waste.

so. Without any transfers, the consumption Gini would have risen by 3 percent and, interestingly, it would have risen already in February due to increased precautionary savings of the poor. The expectation of conditional transfers eliminates this precautionary increase in consumption inequality—illustrating also in terms of this statistic the strong insurance effect of the FPUC payments.

Hence, the transfers under the CARES act did not only contribute to stabilize economic activity. They also limited its fallout in terms of economic inequality. In a last step, we briefly assess their impact in terms of welfare. The left panel of Figure 9 shows the one-sided welfare effects of the pandemic had there been no transfers. All households lose, but, comparing along the wealth dimension, the welfare loss is the smallest for wealthy households that have the means to self insure. Comparing along the income dimension (within wealth group), the high productivity households lose more despite the fact that they have a lower incidence of quarantine. Their lifetime income suffers more from lower current factor prices. When it comes to the gains from transfers (right panel), the picture partly reverses. Still, the wealthy households gain relatively little from the transfers because they do not need the extra insurance. However, when stratifying by income, it is the low income households who gain most from transfers. In terms of lifetime income as well as current income, the CARES transfers more substantially boost the income of the poor than the income of the rich.<sup>25</sup>

<sup>25</sup>Note that, on average, the CARES transfers overcompensate welfare losses due to the pandemic. This reflects the assumption that the increased transfers are financed by cuts in future government expenditures which the model treats as pure waste in welfare terms. A more detailed welfare analysis would require knowledge of how the transfers will be ultimately financed and the welfare consequences thereof.

## 5 Conclusion

How large is the transfer multiplier? As often, the answer is: “it depends.” For the effects of the transfer payments implemented under the CARES Act differ fundamentally depending on whether transfers are conditional on the recipient being unemployed or not. We obtain this result as we study the COVID-19 recession and the fiscal transfers through the lens of a medium-scale HANK model. We calibrate the model to capture the developments of the unemployment rate during 2020/21 as well as the fiscal transfers payments of the Coronavirus stimulus package. We find that our model replicates well key feature of the data, both along the time-series dimension and the cross-section of households.

To understand the effect of transfers, we rely on counterfactual model simulations. We find, in particular, that conditional transfers (under the FPUC scheme) are effective in stabilizing the aggregate economy, given the conditions under study, while unconditional transfers are not. This is noteworthy for a number of reasons, including the fact that both transfer components were of about the same size in the Coronavirus stimulus package. Conditional transfers are particular effective because they are directed to the unemployed who have a high marginal propensity to consume. In addition, as our analysis highlights, they limit income risk associated with unemployment and thus help to avoid recessionary spirals of precautionary savings. Finally, we find that the conditional transfers helped to contain the increase of inequality caused by the COVID-19 recession as well its adverse welfare effects on the poor.

Transfers to households were only a part of the fiscal stimulus under the CARES Act. Among other things, it also provided for transfers to firms. It would be interesting to assess the impact of these policies as well as other fiscal-policy measures implemented in countries outside of the U.S. As our current analysis makes clear, the effect of such measures is bound to interact in non-trivial ways with the specific conditions and institutions under which they are put in place. We leave a more comprehensive analysis for future research.

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## A Data

Unless otherwise noted, all series available from the St.Louis FED - FRED database (mnemonics in parentheses).

### A.1 Calibration

Averages computed on 1981–2019 sample unless otherwise noted.

**Mean illiquid assets.** Fixed assets (NIPA table 1.1) over quarterly GDP (excluding net exports; see below).

**Mean liquidity.** Federal debt held by the public as percent of Gross Domestic Product (FYGFGDQ188S).

**Fraction of borrowers.** Taken from the Survey of Consumer Finances (1983-2013); see Bayer et al. (2019) for more details.

**Average top 10% share of wealth.** Source is the World Inequality Database.

### A.2 Data figures

Unless otherwise noted, series are detrended by HP-filter ( $\lambda = 129600$ ). Quarterly series are transformed to monthly frequency via cubic spline interpolation.

**Initial claims.** Monthly sum of weekly initial claims (ICSA).

**Unemployment rate.** Monthly unemployment rate (UNRATE).

**Unemployment rate: low income.** Monthly unemployment rate - high school graduates or less, no college, 25 yrs. & over (LNS14027660).

**Unemployment rate: middle income.** Monthly unemployment rate - some college or associate degree, 25 yrs. & over (LNS14027689).

**Unemployment rate: high income.** Monthly unemployment rate - bachelor's degree and higher, 25 yrs. & over (LNS14027662).

**Output.** Sum of gross fixed capital formation (USAGFCFQDSMEI), personal consumption expenditures (PCE), and government consumption expenditures and gross investment (GCE) divided by the GDP deflator (GDPDEF).

**Consumption.** Personal consumption expenditures (PCE) divided by the GDP deflator (GDPDEF).

**Investment.** Gross fixed capital formation (USAGFCFQDSMEI) divided by the GDP deflator (GDPDEF).

**Debt-to-output ratio.** Federal debt held by the public as percent of Gross Domestic Product (FYGFGDQ188S).

**Inflation.** Month-on-month percent change (annualized) in the consumer price index for all urban consumers: all items in U.S. city average (CPIAUCSL).

**Policy rate.** Effective federal funds rate (FEDFUNDS) – not detrended.

### A.3 CARES

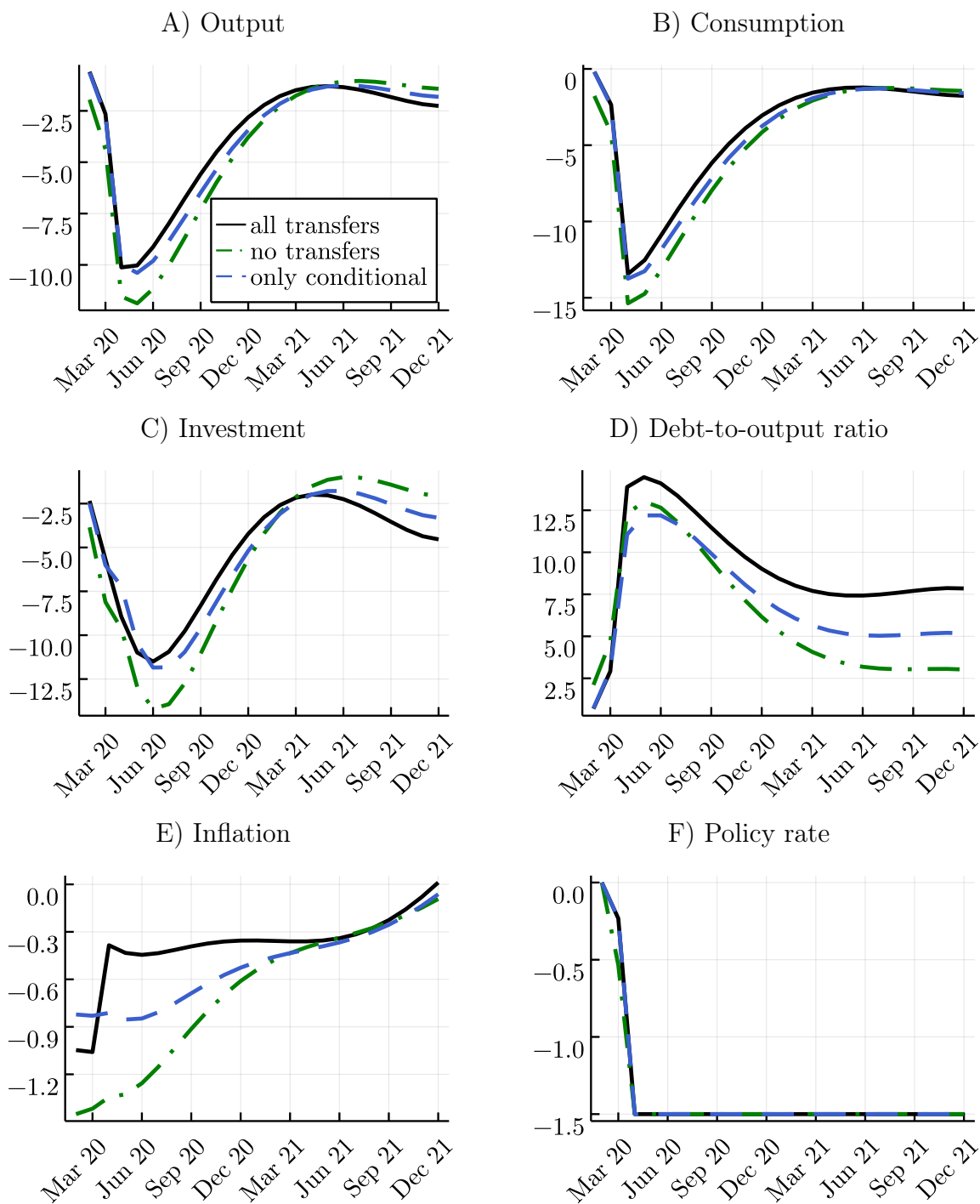
**Conditional transfers – FPUC.** Pandemic Unemployment Compensation Payments taken from BEA Personal Income Statistics.

**Unconditional transfers.** CARES legislation according to the Congressional Budget Office.

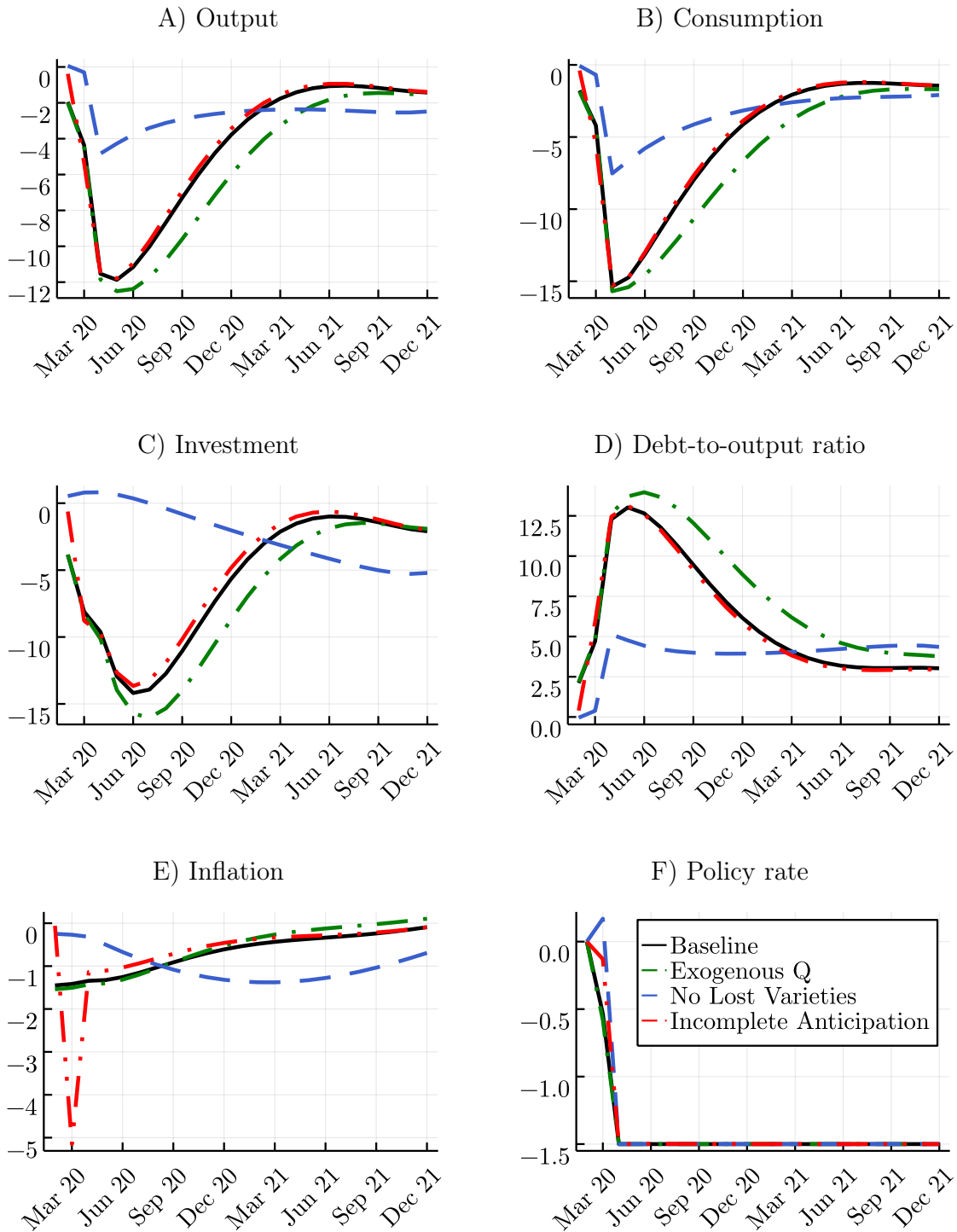
## B Additional Figures

Figure A.1 provides counterfactuals to the IRFs from Figure 4 of the main text. It shows how the economy would have reacted in absence of certain elements of the CARES package. The solid black line is the baseline with all transfers active, the blue dashed line shows a counterfactual without unconditional transfers and the green dashed-dotted line the counterfactual without any additional transfers and only regular unemployment benefits in place.

Figure A.2 provides results for alternative model specifications in order to analyze the importance of certain model aspects and channels. To disentangle model elements and the interaction with the CARES package, we show here the results without any transfers in place. Concretely, we compare the baseline (black solid line) to a setup (1) without feedback from aggregate activity to quarantines,  $\Sigma_{Q,Y} = 0$ , (green dash-dotted line), (2) where no goods are quarantined (blue dashed line), and (3) where the shocks of March and April are unexpected in February such that  $\mathbb{E}_t(\epsilon_{t+1}^Q) = 0$  for all  $t$  and the full path of the quarantine risk is only revealed by April (red dash-double-dotted line). This implies, in particular, less risk of quarantine for May than anticipated in March.



**Figure A.1:** Decomposition of dynamic adjustment to Q-shock. Notes: Black solid line shows baseline response w/ conditional and unconditional transfers, green dash-dotted line w/o CARES transfers, and blue dashed line w/ conditional transfer only. For variable descriptions, see Figure 4. Y-axis: Percentage deviation from steady state, annualized percentage points in case of (m-o-m) inflation and interest rate. X-axis: Months.



**Figure A.2:** Dynamic adjustment to alternative Q-shock specifications w/o CARES transfers. Notes: Impulse responses to baseline Q-shock (black solid line), Q-shock w/o feedback from aggregate activity to quarantines (green dash-dotted line), Q-shock when no goods are quarantined (blue dashed line), and Q-shock when full path is only revealed in April (red dash-double-dotted line). For variable descriptions, see Figure 4. Y-axis: Percentage deviation from steady state, annualized percentage points in case of (m-o-m) inflation and interest rate. X-axis: Months.

## C Dealing with COVID Waves

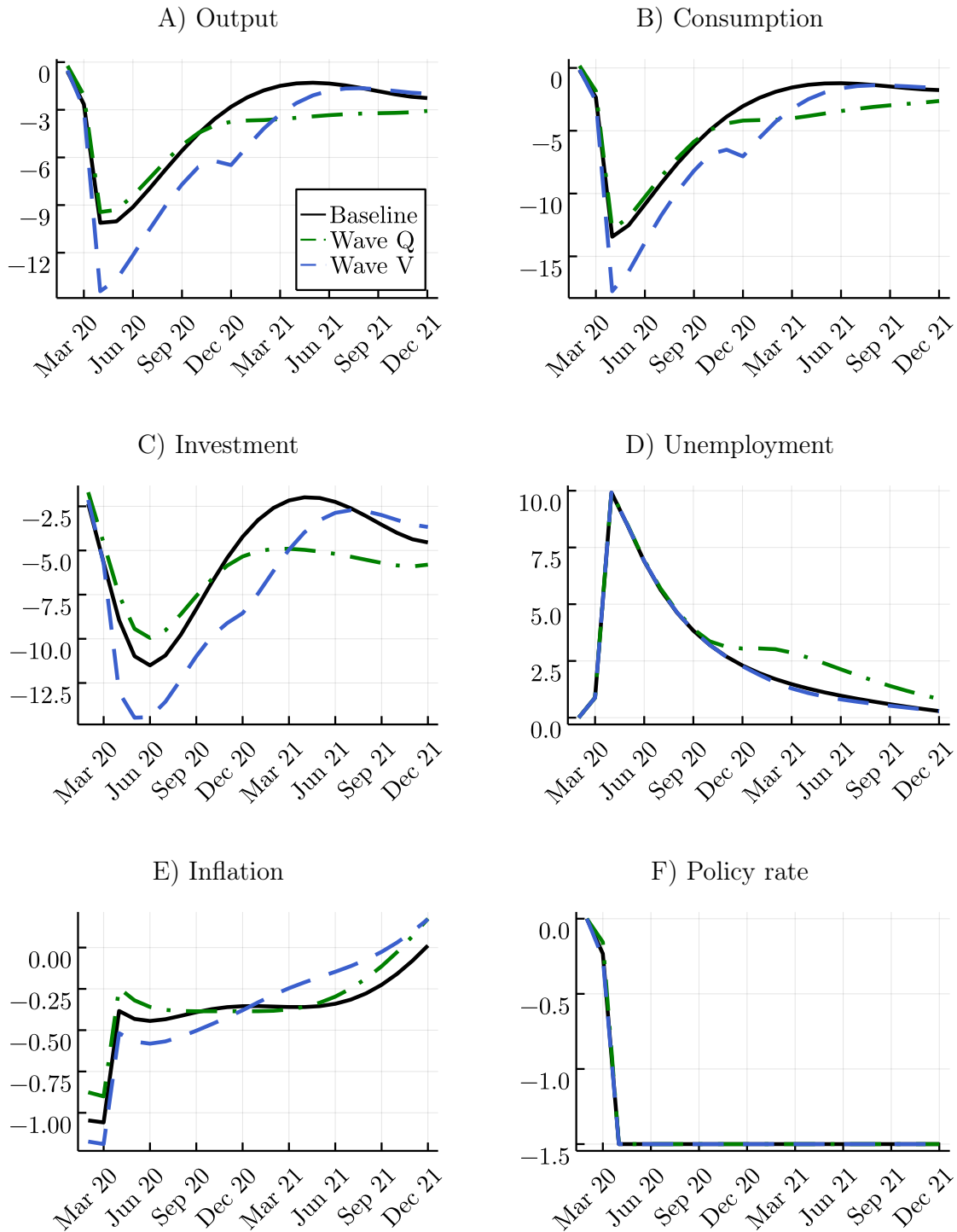
To check whether the recurrent nature of COVID (waves) affects our results, we build two additional scenarios. The first scenario follows our baseline calibration strategy to match the unemployment rate and view all quarantines of workers, capital, and varieties as moving in lockstep. There is a small slowdown of the recovery of the unemployment rate in autumn 2020. This means, we adjust the Q-shock accordingly and add shocks,  $\epsilon_t^Q$ , to the Q-Process, Equation (2), of 0.1% in Oct20, 0.25% in Nov20, 0.2% in Dec20, 0.2% in Jan21, and 0.1% in Feb21. As in the baseline, the path of Q including the 2nd wave is known in advance.

The second alternative builds on the observation that autumn 2020 saw a stronger lock-down of varieties than movement in unemployment, if one looks at, say, evidence from restaurant visits and movement in general, see e.g. Bognanni et al. (2020). Here, we keep the Q-shock as in the baseline, but allow for additional independent shocks to the available varieties of final goods (Wave-V). These shocks follow a log-AR(1) process, too,  $Q_t^V = \exp(\rho_{Q^V} \log Q_{t-1}^V + \epsilon_t^{Q^V})$ , and affect the offer of varieties on top of what the baseline quarantines do, such that  $Y_t = [Q_t^V \bar{H}_t]^{\frac{1}{\eta_S-1}} Y_t^F$  and  $\frac{P_t}{P_t^F} = [Q_t^V \bar{H}_t]^{\frac{1}{\eta_S-1}}$ . We reduce the availability of varieties by -1% in Nov20 and -3% in Dec20, and let the process follow its autocorrelation ( $\rho_{Q^V} = 0.7$ ) thereafter. This is designed to match the drop in consumption of 1% in Dec20. Again the full path of  $Q_t^V$  is known in advance. The goal of this alternative therefore is to test the robustness of the multipliers to the existence of a second wave.

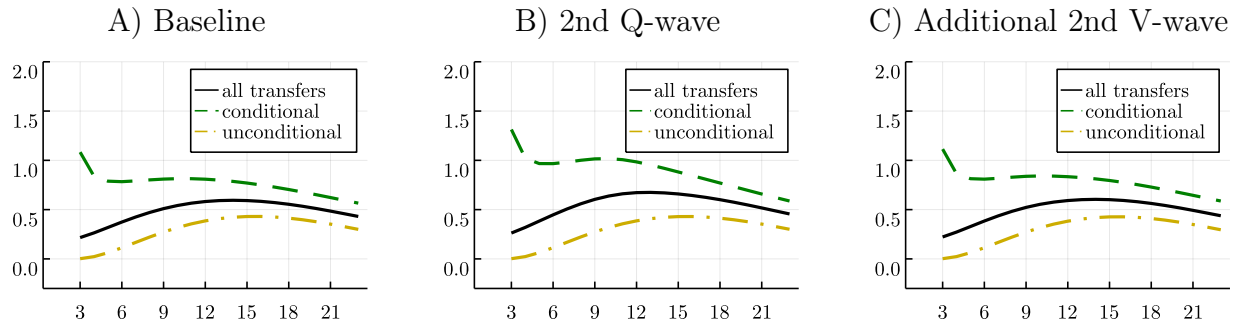
Wave-Q does not create the second, but small, dip in consumption in autumn 2020, but still slows down the recovery in 2021, see Figure A.3. The figure shows the response including CARES. Overall the effect is small because the extra unemployment wave is small to start with. Wave-V does, by construction, replicate the additional contraction of consumption by -1% in Dec20. It also increases the size of the trough in Apr20 by some 30%.

By and large, the established picture reemerges for the multipliers. The fiscal transfer multiplier becomes slightly higher in the case of Wave-Q, see Figure A.4, because additional Q-shocks increase income risk in the autumn of 2020. However, somewhat counterfactually, this assumes the CARES-2020-FPUC transfers to be paid out to the new quarantines in autumn, too. Wave-V, by contrast, does not affect the multiplier. This is in line with our findings from Figure 7, where the multipliers remain unchanged without lost varieties. Fluctuations in varieties do not interfere with MPCs and income risk that are the key drivers of the transfer multipliers.

The recurrent nature of COVID-19 is not of first-order importance for the size of the transfer multiplier in the US because the second wave of lockdowns shows up hardly in the unemployment rate. If at all, it shows up in reduced varieties leaving multipliers unchanged.



**Figure A.3:** Dynamic adjustment to alternative 2nd-wave specifications. Notes: Impulse responses to baseline Q-shock (no 2nd wave, black solid line), Q-shock with 2nd Q-wave (green dash-dotted line), baseline Q-shock with an additional 2nd wave in lost varieties (blue dashed line); see text for details. For variable descriptions, see Figure 4. Y-axis: Percentage deviation from steady state, annualized percentage points in case of (m-o-m) inflation and interest rate. X-axis: Months.



**Figure A.4:** Multiplier dependence on 2nd-wave. Notes: left panel replicates the baseline multipliers. Center panel shows multipliers with a second wave in Q. Right panel shows multipliers with a second wave that only affects varieties; see text for details. X-axis: months after start of pandemic.