

Modeling the Consumption Response to the CARES Act

April 17, 2020

Christopher D. Carroll¹
JHU

Edmund Crawley²
FRB

Jiri Slacalek³
ECB

Matthew N. White⁴
UDel

Abstract

To predict the effects of the 2020 U.S. ‘CARES’ act on consumption, we extend a model that matches responses of households to past consumption stimulus packages. The extension allows us to account for two novel features of the coronavirus crisis. First, during the lockdown, many types of spending are undesirable or impossible. Second, some of the jobs that disappear during the lockdown will not reappear when it is lifted. We estimate that, if the lockdown is short-lived, the combination of expanded unemployment insurance benefits and stimulus payments should be sufficient to allow a swift recovery in consumer spending to its pre-crisis levels. If the lockdown lasts longer, an extension of will likely be necessary if consumption spending is to recover.

Keywords Consumption, Coronavirus, Stimulus

JEL codes D83, D84, E21, E32

econ-ark.github.io/Pandemic *HTML version of paper*
[Interactive-Jupyter-Notebook](#) *Allows user to modify some assumptions*
github.com/econ-ark/Pandemic *Full codebase; configurator to explore all assumptions*

¹Carroll: Department of Economics, Johns Hopkins University, <http://econ.jhu.edu/people/ccarroll/>, ccarroll@jhu.edu ²Crawley: Federal Reserve Board, edmund.s.crawley@frb.gov ³Slacalek: DG Research, European Central Bank, <http://www.slacalek.com/>, jiri.slacalek@ecb.europa.eu ⁴White: Department of Economics, University of Delaware, mwcon@udel.edu

Thanks to the Sloan foundation for funding of the [Econ-ARK](<https://econ-ark.org>) toolkit. We are grateful to Kiichi Tokuoka, who provided valuable feedback and input as this project progressed, and to Mridul Seth, who created the dashboard and configurator. The computational results in this paper were constructed using tools in the Econ-ARK/HARK toolkit. The toolkit can be cited by its digital object identifier, [10.5281/zenodo.1001068](https://doi.org/10.5281/zenodo.1001068), as is done in the paper’s own references as Carroll, White, and Econ-ARK (2017). The views presented in this paper are those of the authors, and should not be attributed to the Federal Reserve Board or the European Central Bank.

“Economic booms are all alike; each recession contracts output in its own way.”

— with apologies to Leo Tolstoy

I Introduction

In the decade since the Great Recession, macroeconomics has made great progress by insisting that models be consistent with microeconomic evidence about household behavior (see Krueger, Mitman, and Perri (2016) for a survey). Starting with one of the new generation of models that focused on reconciling apparent conflicts between micro and macro evidence about consumption dynamics¹ (and that specifically matches evidence about responses to past stimulus packages, we add two features to adapt it to model the coronavirus crisis. First, because the tidal wave of layoffs for employees of shuttered businesses will have a large impact on their income and spending, assumptions must be made about the employment dynamics of laid off workers. Second, even consumers who remain employed will have restricted spending options (nobody can eat dinner at a shuttered restaurant).

On the first count, we model the likelihood that many of the people unemployed during the lockdown will be able to quickly return to their old jobs (or similar ones) by assuming that the typical job loser has a two-thirds chance of being reemployed in the same or a similar job after each quarter of unemployment. However, we expect that some kinds of jobs will not come back quickly after the lockdown,² and that people who worked in these kinds of jobs will have more difficulty finding a new job. We call these people the ‘deeply unemployed’ and assume that there is a one-third chance each quarter that they become merely ‘normal unemployed’. The ‘normal unemployed’ have a jobfinding rate that matches average historical unemployment spell of 1.5 quarters. Thus a deeply unemployed person expects to remain that way for three quarters on average, and then unemployed for another one and a half quarters. When the pandemic hits, 10 percent of model households become normal unemployed and an additional 5 percent become deeply unemployed; in line with empirical evidence, the unemployment probabilities are skewed toward households who are young, unskilled and have low income.

On the second count, we model the restricted spending options by assuming that during the lockdown spending money is less enjoyable (there is a negative shock to the ‘marginal utility of consumption.’) Based on a tally of sectors that we judge to be substantially shuttered during the ‘lockdown,’ we calibrate an 11 percent reduction to spending. Thus households will prefer to defer some of their consumption into the future, when it will yield them greater utility. (See Carvalho, Garcia, Hansen, Ortiz, Rodrigo, Rodriguez, and Ruiz (2020) for Spanish data already showing a strong effect of this kind in recent weeks). In our primary scenario, we assume that this condition is removed with probability one-half after each quarter, so on average remains for two quarters. When the ‘lockdown’ ends, the buildup of savings by households who did not lose their jobs but whose spending was suppressed should result in a partial recovery in consumer

¹Havranek, Rusnak, and Sokolova (2017).

²The cruise industry, for example, is likely to take a long time to recover.

spending, but in our primary scenario (without the CARES act), total consumer spending remains below its pre-crisis peak through the foreseeable future.

Our model captures the two primary features of the CARES Act that aim to bolster consumer spending:

1. The boost to unemployment insurance benefits, amounting to \$7,800 if unemployment lasts for 13 weeks.
2. The direct stimulus payments to households, amounting to \$1,200 per adult.

We estimate that the combination of expanded unemployment insurance benefits and stimulus payments should be sufficient to allow a swift recovery in consumer spending to its pre-crisis levels under our primary scenario in which the lockdown ends after two quarters on average. Overall, unemployment benefits account for about 30 percent of the total aggregate consumption response and stimulus payments explain the remainder.

Our analysis partitions households into three groups based on their employment state when the pandemic strikes and the lockdown begins.

First, households in our model who do not lose their jobs will initially build up their savings, both because of the lockdown-induced suppression of spending and because most of these households will receive a significant stimulus check, much of which the model says will be saved. Even without the lockdown, we estimate that only about 20 percent of the stimulus money would be spent immediately upon receipt, consistent with evidence from prior stimulus packages about spending on nondurable goods and services. Once the lockdown ends, the spending of the always-employed households rebounds strongly thanks to their healthy household finances.

The second category of households are the ‘normal unemployed,’ job losers who perceive that it is likely they will be able to resume their old job (or get a similar new job) when the lockdown is over. Our model predicts that the CARES Act will be particularly effective in stimulating their consumption, given the perception that their income shock will be largely transitory. Our model predicts that by the end of 2021, the spending of this group will recover to the level it would have achieved in the absence of the pandemic (‘baseline’); without the CARES Act, this recovery would take more than a year longer.

Finally, for households in the deeply unemployed category, our model says that the marginal propensity to consume (MPC) from the checks will be considerably smaller, because they expect to have to stretch that money for longer. Even with the stimulus from the CARES Act, we predict that consumption spending for these households will not fully recover until the middle of 2023. Even so, the act makes a big difference to their spending, particularly in the first six quarters after the crisis. For both groups of unemployed households, the effect of the stimulus checks is dwarfed by the increased unemployment benefits, which arrive earlier and are much larger (per recipient).

Perhaps surprisingly, we find the effectiveness of the combined stimulus checks and unemployment benefits package for aggregate consumption is not substantially different from a package that distributed the same quantity of money equally

between households. The reason for this is twofold: first, the extra unemployment benefits in the CARES Act are generous enough that many of the ‘normally’ unemployed remain financially sound and can afford to save a good portion of those benefits; second, the deeply unemployed expect their income to remain depressed for some time and therefore save more of the stimulus for the future. In the model, the fact that they do *not* spend immediately is actually a reflection of how desperately they anticipate these funds will be needed to make it through a long period of uncertainty. While unemployment benefits do not strongly stimulate current consumption of the deeply unemployed, they do provide important disaster relief for those who may not be able to return to work for several quarters (see Krugman (2020) for an informal discussion).

In addition to our primary scenario’s relatively short lockdown period, we also consider a worse scenario in which the lockdown is expected to last for four quarters and the unemployment rate increases to 20 percent. In this case, we find that the return of spending toward its no-pandemic path takes roughly three years. Moreover, the spending of deeply unemployed households will fall steeply unless the temporary unemployment benefits in the CARES Act are extended for the duration of the lockdown.

Our modeling assumptions — about who will become unemployed, how long it will take them to return to employment, and the direct effect of the lockdown on consumption utility — are not ironclad. Reasonable analysts may differ on all of these points, and prefer a different calibration. To encourage such exploration, we have made available our modeling and prediction software, with the goal of making it easy for fellow researchers to test alternative assumptions. Instructions for installing and running our code can be found [here](#); alternatively, you can explore adjustments to our parametrization with an interactive dashboard [here](#).

Existing Work on the Effects of the Pandemic

Many papers have recently appeared on the economic effects of the pandemic and policies to manage it. Several papers combine the classic susceptible–infected–recovered (SIR) epidemiology model with dynamic economic models to study the interactions between health and economic policies (Eichenbaum, Rebelo, and Trabandt (2020) and Alvarez, Argente, and Lippi (2020), among others). Guerrieri, Lorenzoni, Straub, and Werning (2020) shows how an initial supply shock (such as a pandemic) can be amplified by the reaction of aggregate demand. The ongoing work of Kaplan, Moll, and Violante (2020) allows for realistic household heterogeneity in how household income and consumption are affected by the pandemic. Glover, Heathcote, Krueger, and Ríos-Rull (2020) studies distributional effects of optimal health and economic policies. Closest to our paper, work analyzing the effects of the fiscal response to the pandemic includes Faria-e-Castro (2020b), in a two-agent DSGE model, and Bayer, Born, Luetticke, and Müller (2020) in a HANK model.

All of this work accounts for general equilibrium effects on consumption and employment, which we omit, but none of it is based on a modeling framework

explicitly constructed to match micro and macroeconomic effects of past stimulus policies, as ours is.

A separate strand of work focuses on empirical studies of how the economy reacts to pandemics; see, e.g., Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020), Jorda, Singh, and Taylor (2020) and Correia, Luck, and Verner (2020).

II Modeling Setup

A The Baseline Model

Our model extends a class of models explicitly designed to capture the rich empirical evidence on heterogeneity in the marginal propensity to consume (MPC) across different types of household (employed, unemployed; young, old; rich, poor). This is motivated by the fact that the act distributes money unevenly across households, particularly targeting unemployed households. A model that does not appropriately capture both the degree to which the stimulus money is targeted, and the differentials in responses across differently targeted groups, is unlikely to produce believable answers about the spending effects of the stimulus.

Specifically, we use a **lifecycle model** calibrated to match the income paths of high school dropouts, high school graduates, and college graduates.³ Households are subject to permanent and transitory income shocks, as well as unemployment spells.⁴ Within each of these groups, we construct an ex ante distribution of discount factors to match their distribution of liquid assets. Matching the distributions of liquid assets allows us to achieve a realistic distribution of marginal propensities to consume according to education group, age, and unemployment status, and thus to assess the impact of the act for these different groups.⁵

B Adaptations to Capture the Pandemic

To model the pandemic, two new features are introduced to the model.

First, our new category of ‘deeply unemployed’ households was created to capture the likelihood that the pandemic will have long-lasting effects on some kinds of businesses and jobs (e.g., the cruise industry), even if the CARES act manages to successfully cushion much of the financial hit to total household income.

Each quarter, our ‘deeply unemployed’ households have a two-thirds chance of remaining deeply unemployed, and a one-third chance of becoming ‘normal unemployed.’ The expected time to employment for a ‘deeply unemployed’ household is four and a half quarters, much longer than the historical average length of a typical unemployment spell. Reflecting recent literature on the ‘scarring effects’ of unemployment spells, permanent income of both ‘normal’ and ‘deeply’ households declines by 0.5 percent each quarter due to ‘skill rot’ (rather than following its usual age profile).

³The baseline model is very close to the lifecycle model in Carroll, Slacalek, Tokunaka, and White (2017).

⁴Households exit unemployment with a fixed probability each quarter — the expected length of an unemployment spell is one and a half quarters.

⁵For a detailed description of the model and its calibration see Appendix A.

Second, a temporary negative shock to the **marginal utility of consumption** captures the idea that, during the period of the pandemic, many forms of consumption are undesirable or even impossible.

The pandemic is modeled as an unexpected (MIT) shock, sending many households into both normal and deep unemployment, as well as activating the negative shock to marginal utility. Households understand and respond in a forward-looking way to their new circumstances (according to their beliefs about its duration), but their decisions prior to the pandemic did not account for any probability that it would occur.

Calibration

The calibration choices for the pandemic scenario are very much open for debate. Here we have tried to capture something like median expectations from early analyses, but there is considerable variation in points of view around those medians. Section **III.B** below presents a more adverse scenario with a long lockdown and a larger increase in unemployment.

Unemployment forecasts for Q2 2020 range widely, from less than 10 percent to over 30 percent, but all point to an unprecedented sudden increase in unemployment.⁶ We choose a total unemployment rate in Q2 2020 of just over 15 percent, consisting of five percent ‘deeply unemployed’ and ten percent ‘normal unemployed’ households.

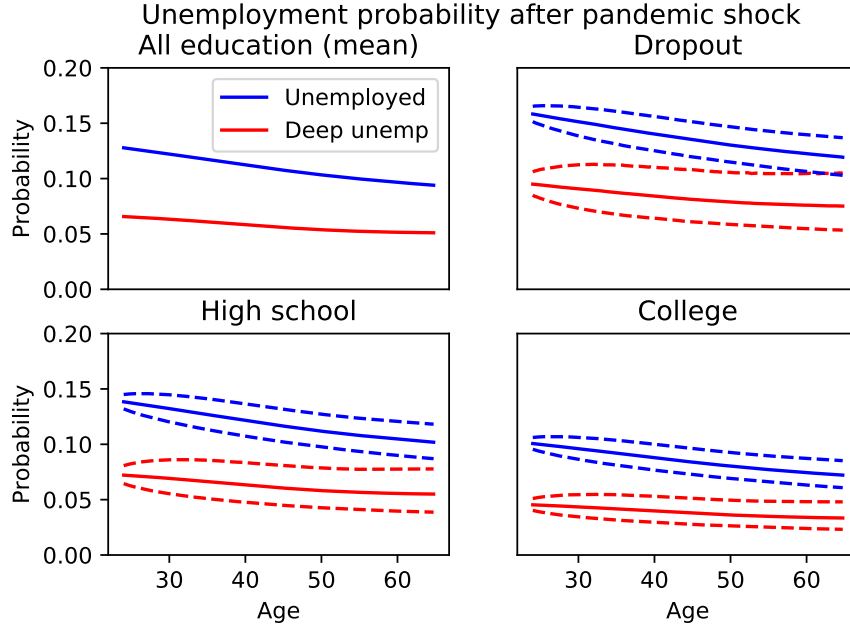
We calibrate the likelihood of becoming unemployed to match empirical facts about the relationship of unemployment to education level, permanent income and age, which is likely to matter because the hardest hit sectors skew young and unskilled.⁷ Figure 1 shows our assumptions on unemployment along these dimensions. In each education category, the solid line represents the probability of unemployment type (‘normal’ or ‘deep’) for a household with the median permanent income at each age, while the dotted lines represent the probability of unemployment type for a household at the 5th and 95th percentile of permanent income at each age; Appendix A with Table A2 detail the parametrization and calibration we used.

To calibrate the drop in marginal utility, we estimate that 10.9 percent of the goods that make up the consumer price index become highly undesirable, or simply unavailable, during the pandemic: food away from home, public transportation including airlines, and motor fuel. We therefore multiply utility from consumption during the period of the epidemic by a factor of 0.891. Furthermore, we choose a one-half probability of exiting the period of lower marginal utility each quarter,

⁶As of April 16, about 22 million new unemployment claims have been filed in four weeks, representing a loss of over 14 percent of total jobs. JP Morgan Global Research forecast 8.5 percent unemployment (JPMorgan (2020), from March 27); Treasury Secretary Steven Mnuchin predicted unemployment could rise to 20 percent without a significant fiscal response (Bloomberg (2020a)); St. Louis Fed president James Bullard said the unemployment rate may hit 30 percent (Bloomberg (2020b)) — see Faria-e-Castro (2020a) for the analysis behind this claim. Based on a survey that closely follows the CPS, Bick and Blandin (2020) calculate a 20.2 percent unemployment rate at the beginning of April.

⁷See Gascon (2020), Leibovici and Santacreu (2020) and Adams-Prassl, Boneva, Golin, and Rauh (2020) for breakdowns of which workers are at most risk of unemployment from the crisis. See additional evidence in Kaplan, Moll, and Violante (2020) and modeling of implications for optimal policies in Glover, Heathcote, Krueger, and Ríos-Rull (2020).

Figure 1 Unemployment Probability in Q2 2020 by Demographics



accounting for the possibility of a ‘second wave’ if restrictions are lifted too early — see Cyranoski (2020).⁸

The CARES Act

We model the two elements of the CARES Act that directly affect the income of households:

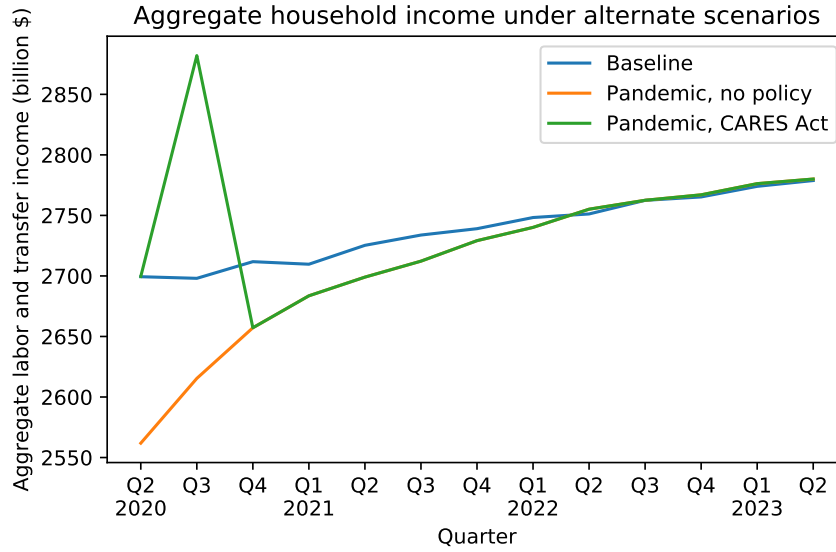
- The stimulus check of \$1,200 for every adult taxpayer, means tested for previous years’ income.⁹
- The extra unemployment benefits of \$600 for up to 13 weeks, a total of \$7,800. For normal unemployed, we assume they receive only \$5,200 to reflect the idea that they may not be unemployed the entire 13 weeks.

We model the stimulus checks as being announced at the same time as the crisis hits. However, only a quarter of households change their behavior immediately at the time of announcement, as calibrated to past experience. The remainder do not respond until their stimulus check arrives, which we assume happens in the following quarter. The households that pay close attention to the announcement of the policy are assumed to be so forward looking that they act as though the

⁸The CBO expects social distancing to last for three months, and predicts it to have diminished, on average and in line with our calibration, by three-quarters in the second half of the year; see Swagel (2020).

⁹The act also includes \$500 for every child. In the model, an agent is somewhere between a household and an individual. While we do not model the \$500 payments to children, we also do not account for the fact that some adults will not receive a check. In aggregate we are close to the Joint Committee on Taxation’s estimate of the total cost of the stimulus checks.

Figure 2 Labor and Transfer Income



payment will arrive with certainty next period; the model even allows them to borrow against it if desired.¹⁰

The extra unemployment benefits are assumed to both be announced and arrive at the beginning of the second quarter of 2020, and we assume that there is no delay in the response of unemployed households to these benefits.

Figure 2 shows the path of labor income — exogenous in our model — in the baseline and in the pandemic, both with and without the CARES Act. Income in quarters Q2 and Q3 2020 is substantially boosted (by around 10 percent) by the extra unemployment benefits and the stimulus checks. After two years, aggregate labor income is almost fully recovered. (See below for a brief discussion of analyses that attempt to endogenize labor supply and other equilibrium variables).

III Results

This section presents our simulation results for the scenario described above. In addition, we then model a more pessimistic scenario with longer lockdown and higher initial unemployment rate.

A Short-lived Pandemic

Figure 3 shows three scenarios for quarterly aggregate consumption: (i) the baseline with no pandemic; (ii) the pandemic with no fiscal response; (iii) the pandemic with both the stimulus checks and extended unemployment benefits in the CARES

¹⁰See Carroll, Crawley, Slacalek, Tokuoka, and White (2020) for a detailed discussion of the motivations behind this way of modeling stimulus payments, and a demonstration that this model matches the empirical evidence of how and when households have responded to stimulus checks in the past — see Parker, Souleles, Johnson, and McClelland (2013), Broda and Parker (2014) and Parker (2017), among others.

Figure 3 Consumption Response to the Pandemic and the Fiscal Stimulus

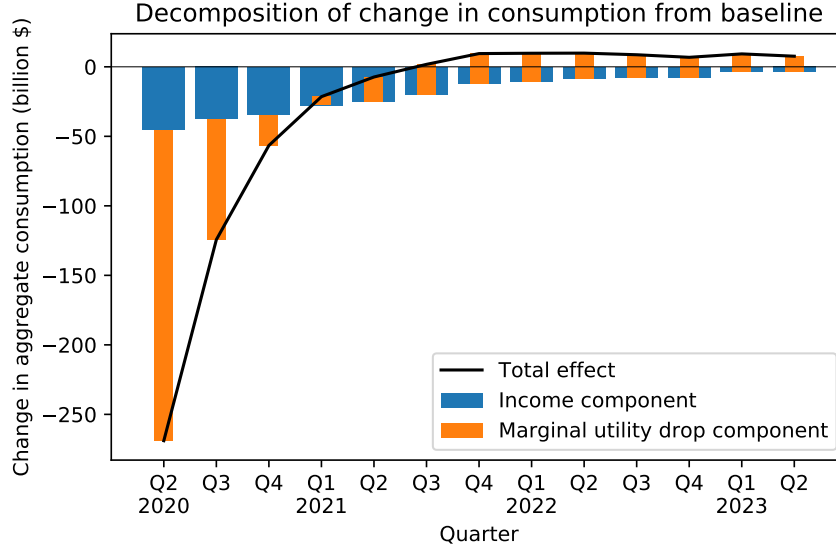


Act. The pandemic reduces consumption by ten percentage points in Q2 2020 relative to the baseline.

Without the CARES Act, consumption remains depressed through to the second half of 2021, at which point spending actually rises above the baseline, as a result of the buildup of liquid assets during the pandemic by households that do not lose their income. We capture the limited spending options during the lockdown period by a reduction in the utility of consumption, which makes household save more than they otherwise would usual during the pandemic, with the result that they build up liquid assets. When the lockdown ends, the pent up savings of the always-employed become available to finance a resurgence in their spending, but the depressed spending of the two groups of unemployed people keeps total spending below the baseline until most of them are reemployed, at which point their spending (mostly) recovers while the always-employed are still spending down their extra savings built up during the lockdown.

Figure 4 decomposes the effect of the pandemic on aggregate consumption (with no fiscal policy response), separating the drop in marginal utility from the reduction in income due to mass layoffs. The figure illustrates that the constrained consumption choices are quantitatively key in capturing the expected depth in the slump of spending, which is already under way; see Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020) and Armantier, Kosar, Pomerantz, Skandalis, Smith, Topa, and van der Klaauw (2020) for early evidence. The marginal utility shock hits all households, and directly affects their spending decisions in the early quarters after the pandemic; its effect cannot be mitigated by fiscal stimulus. The loss of income from unemployment is large, but affects only a fraction of households, who are disproportionately low income and thus account for a smaller share of aggregate consumption. Moreover, most households hold at least some liquid assets, allowing them to smooth their consumption drop — the 5 percent

Figure 4 Decomposition of Effect of the Pandemic on Aggregate Consumption (No Policy Response)



decrease in labor income in Figure 2 induces only a 1.5 percent decrease in consumption in Figure 4.

Figure 5 shows how the consumption response varies depending on the employment status of households in Q2 2020. For each employment category (employed, unemployed, and deeply unemployed), the figure shows consumption relative to the same households' consumption in the baseline scenario with no pandemic (dashed lines).¹¹ The upper panel shows consumption without any policy response, while the lower panel includes the CARES Act. The figure illustrates an important feature of the unemployment benefits that is lost at the aggregate level: the response provides the most relief to households whose consumption is most affected by the pandemic. For the unemployed — and especially for the deeply unemployed — the consumption drop when the pandemic hits is much shallower and returns faster toward the baseline when the fiscal stimulus is in place.

Indeed, this targeted response is again seen in Figure 6, showing the extra consumption relative to the pandemic scenario without the CARES Act. The dashed lines show the effect of the stimulus check in isolation (for employed workers this is the same as the total fiscal response). For unemployed households, this is dwarfed by the increased unemployment benefits. These benefits both arrive earlier and are much larger. Specifically, in Q3 2020, when households receive the stimulus checks, the effect of unemployment benefits on consumption makes up about 70 percent and 85 percent of the total effect for the normally and deeply unemployed, respectively.

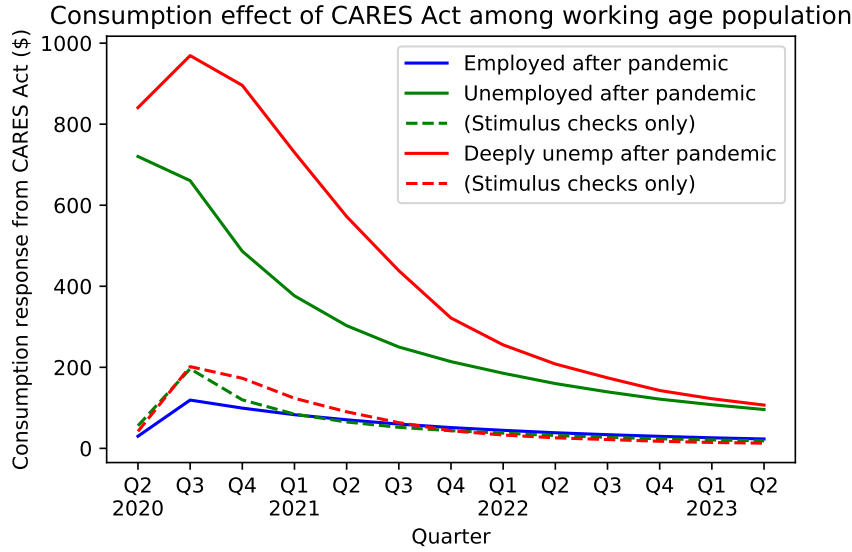
Figure 7 aggregates the decomposition of the CARES Act in Figure 6 across all

¹¹Households that become unemployed during the pandemic might or might not have been unemployed otherwise. We assume that all households that would have been unemployed otherwise are either unemployed or deeply unemployed in the pandemic scenario. However, there are many more households that are unemployed in the pandemic scenario than in the baseline.

Figure 5 Consumption Response by Employment Status



Figure 6 Effect of CARES Act by Employment Status



households. In our model economy, the extra unemployment benefits amount to \$544 per household, while the stimulus checks amount to \$1,054 per household (as means testing reduces or eliminates the stimulus checks for high income households). Aggregated, stimulus checks amount to \$267 billion, while the extended unemployment benefits amount to just over half that, \$137 billion.¹² The figure shows that during the peak consumption response in Q3 2020, the stimulus checks account for about 70 percent of the total effect on consumption for the average household and the unemployment benefits for about 30 percent. Thus, although the unemployment benefits make a much larger difference to the spending of the individual recipients than the stimulus checks, a small enough proportion of households becomes unemployed that the total extra spending coming from these people is less than the total extra spending from the more widely distributed stimulus checks.

The previous graphs show the importance of the targeted unemployment benefits at the individual level, but the aggregate effect is less striking. Figure 8 compares the effect of the CARES Act (both unemployment insurance and stimulus checks) to a policy of the same absolute size that distributes checks to everybody. While unemployment benefits arrive sooner, resulting in higher aggregate consumption in Q2 2020, the un-targeted policy leads to higher aggregate consumption in the following quarters.

The interesting conclusion is that, while the net spending response is similar for alternative ways of distributing the funds, the choice to extend unemployment benefits means that much more of the extra spending is coming from the people who will be worst hurt by the crisis. This has obvious implications for the design of any further stimulus packages that might be necessary if the crisis lasts longer than our baseline scenario assumes.

¹²See Appendix B for details on how we aggregate households.

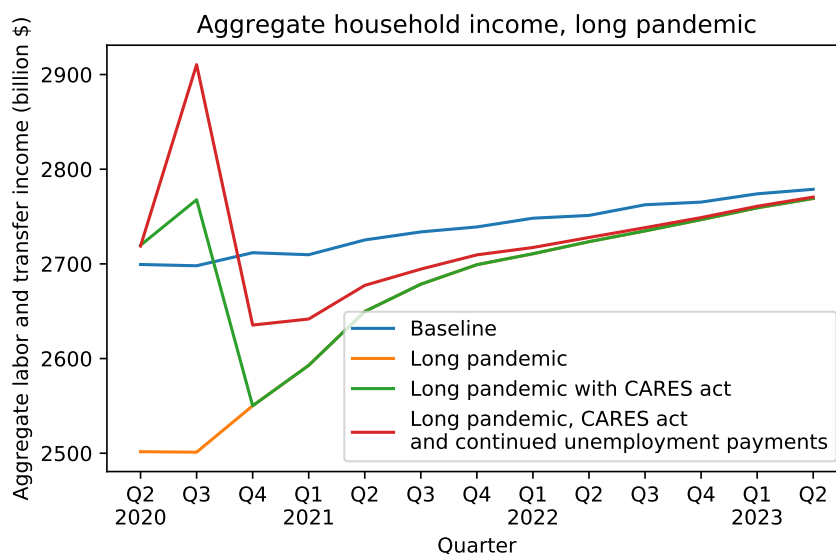
Figure 7 Aggregate Consumption Effect of Stimulus Checks vs Unemployment Benefits



Figure 8 Effect of Targeting the CARES Act Consumption Stimulus



Figure 9 Labor and Transfer Income During the Long, Four-Quarter Pandemic



B Alternative Scenario: Long, Deep Pandemic

Given the uncertainty about how long and deep the current recession will be, we investigate a more pessimistic scenario in which the lockdown is expected to last for four quarters. In addition, the unemployment rate will increase to 20 percent, consisting of 15 percent of deeply unemployed and 5 percent of normal unemployed. In this scenario we compare how effectively the CARES package stimulates consumption, also considering a more generous plan in which the unemployment benefits continue until the lockdown is over. We model the receipt of unemployment benefits each quarter as an unexpected shock, representing a series of policy renewals.

Figure 9 compares the effects of the two fiscal stimulus scenarios on income. The persistently high unemployment results in a substantial and long drop in aggregate income (orange), compared to the no pandemic scenario. The CARES stimulus (green) provides only a short term support to income for the first two quarters. In contrast, the scenario with unemployment benefits extended as long as the lockdown lasts (red) keeps aggregate income elevated through the recession.

Figure 10 shows the implications of the two stimulus packages for aggregate consumption. The long lockdown causes a much longer decline in spending than the shorter lockdown in our primary scenario. In the shorter pandemic scenario (Figure 3) consumption returns to the baseline path after roughly one year, while in the long lockdown shown here the recovery takes around three years; that is, the CARES stimulus shortens the consumption drop to about 2 years. The scenario with extended unemployment benefits ensures that aggregate spending returns to the baseline path after roughly one year, and does so by targeting the funds to the people who are worst hurt by the crisis and to whom the cash will make the most difference.

Figure 10 Consumption Response to the Long, Four-Quarter Pandemic



IV Conclusions

Our model suggests that there may be a strong consumption recovery when the social-distancing requirements of the pandemic begin to subside. We invite readers to test the robustness of this conclusion by using the associated software toolkit to choose their own preferred assumptions on the path of the pandemic, and of unemployment, to understand better how consumption will respond.

One important limitation of our analysis is that it does not incorporate Keynesian demand effects or other general equilibrium responses to the consumption fluctuations we predict. In practice, Keynesian effects are likely to cause movements in aggregate income in the same direction as consumption; in that sense, our estimates can be thought of as a “first round” analysis of the dynamics of the crisis, which will be amplified by any Keynesian response. These considerations further strengthen the case that the CARES Act will make a substantial difference to the economic outcome. A particularly important consideration is that forward-looking firms that expect consumer demand to return forcefully in the third and fourth quarters of 2020 are more likely to maintain relations with their employees so that they can restart production quickly.

The ability to incorporate Keynesian demand effects is one of the most impressive achievements of the generation of heterogeneous agent macroeconomic models that have been constructed in the last few years. But the technical challenges of constructing those models are such that they cannot yet incorporate realistic treatments of features that our model says are quantitatively important, particularly differing risks of (and types of) unemployment, for different kinds of people (young, old; rich, poor; high- and low-education). This rich heterogeneity is important both to the overall response to the CARES act, and to making judgments about the extent to which it has been targeted to provide benefits to

those who need them most. A fuller analysis that incorporates both the kinds of heterogeneity that are of interest to policymakers and a satisfying treatment of general equilibrium will have to wait for another day, but that day is likely not far off.

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Appendices

A Model Details

The baseline model is adapted and expanded from Carroll, Slacalek, Tokuoka, and White (2017). The economy consists of a continuum of expected utility maximizing households with a common CRRA utility function over consumption, $u(\mathbf{c}, \eta) = \eta \mathbf{c}^{1-\rho} / (1 - \rho)$, where η is a marginal utility shifter. Households are *ex ante* heterogeneous: household i has a quarterly time discount factor $\beta_i \leq 1$ and an education level $e_i \in \{D, HS, C\}$ (for dropout, high school, and college, respectively). Each quarter, the household receives (after tax) income, chooses how much of their market resources \mathbf{m}_{it} to consume \mathbf{c}_{it} and how much to retain as assets \mathbf{a}_{it} ; they then transition to the next quarter by receiving shocks to mortality, income, their employment state, and their marginal utility of consumption.

For each education group e , we assign a uniform distribution of time preference factors between $\beta_e - \nabla$ and $\beta_e + \nabla$, chosen to match the distribution of liquid wealth and retirement assets. Specifically, the calibrated values in Table A1 fit the ratio of liquid wealth to permanent income in aggregate for each education level, as computed from the 2004 Survey of Consumer Finance. The width of the distribution of discount factors was calibrated to minimize the difference between simulated and empirical Lorenz shares of liquid wealth for the bottom 20%, 40%, 60%, and 80% of households, as in Carroll, Slacalek, Tokuoka, and White (2017).

When transitioning from one period to the next, a household with education e that has already lived for j periods faces a D_{ej} probability of death. The quarterly mortality probabilities are calculated from the Social Security Administration’s actuarial table (for annual mortality probability) and adjusted for education using Brown, Liebman, and Pollett (2002); a household dies with certainty if it (improbably) reaches the age of 120 years. The assets of a household that dies are completely taxed by the government to fund activities outside the model. Households who survive to period $t + 1$ experience a return factor of R on their assets, assumed constant.

Household i ’s state in period t , at the time it makes its consumption–saving decision, is characterized by its age j ,¹³ a level of market resources $\mathbf{m}_{it} \in \mathbb{R}_+$, a permanent income level $\mathbf{p}_{it} \in \mathbb{R}_{++}$, a discrete employment state $\ell_{it} \in \{0, 1, 2\}$ (indicating whether the individual is employed, normal unemployed, or deeply unemployed), and a discrete state $\eta_{it} \in \{1, \underline{\eta}\}$ that represents whether its marginal utility of consumption has been temporarily reduced ($\underline{\eta} < 1$). Denote the joint discrete state as $n_{it} = (\ell_{it}, \eta_{it})$.

Each household inelastically participates in the labor market when it is younger than 65 years ($j < 164$) and retires with certainty at age 65. The transition from working life to retirement is captured in the model by a one time large decrease in permanent income at age $j = 164$.¹⁴ Retired households face essentially no income

¹³Households enter the model aged 24 years, so model age $j = 0$ corresponds to being 24 years, 0 quarters old.

¹⁴The size of the decrease depends on education level, very roughly approximating the progressive structure of Social Security: $\Gamma_{D164} \approx 0.56$, $\Gamma_{HS164} \approx 0.44$, $\Gamma_{C164} \approx 0.31$.

risk: they receive Social Security benefits equal to their permanent income with 99.99% probability and miss their check otherwise; their permanent income very slowly degrades as they age. The discrete employment state ℓ_{it} is irrelevant for retired households.

Labor income for working age households is subject to three risks: unemployment, permanent income shocks, and transitory income shocks. Employed ($\ell_{it} = 0$) households' permanent income grows by age-education-conditional factor Γ_{ej} on average, subject to a mean one lognormal permanent income shock ψ_{it} with age-conditional underlying standard deviation of $\sigma_{\psi j}$. The household's labor income \mathbf{y}_{it} is also subject to a mean one lognormal transitory shock ξ_{it} with age-conditional underlying standard deviation of $\sigma_{\xi j}$. The age profiles of permanent and transitory income shock standard deviations are approximated from the results of Sabelhaus and Song (2010), and the expected permanent income growth factors are adapted from Cagetti (2003). Normal unemployed and deeply unemployed households receive unemployment benefits equal to a fraction $\underline{\xi} = 0.3$ of their permanent income, $\mathbf{y}_{it} = \underline{\xi}\mathbf{p}_{it}$; they are not subject to permanent nor transitory income risk, but their permanent income degrades at rate $\underline{\Gamma}$, representing "skill rot".¹⁵

The income process for a household can be represented mathematically as:

$$\mathbf{p}_{it} = \begin{cases} \psi_{it}\Gamma_{ej}\mathbf{p}_{it-1} & \text{if } \ell_{it} = 0, j < 164 & \text{Employed, working age} \\ \underline{\Gamma}\mathbf{p}_{it-1} & \text{if } \ell_{it} > 0, j < 164 & \text{Unemployed, working age ,} \\ \Gamma_{ret}\mathbf{p}_{it-1} & \text{if } j \geq 164 & \text{Retired} \end{cases}$$

$$\mathbf{y}_{it} = \begin{cases} \xi_{it}\mathbf{p}_{it} & \text{if } \ell_{it} = 0, j < 164 & \text{Employed, working age} \\ \underline{\xi}\mathbf{p}_{it} & \text{if } \ell_{it} > 0, j < 164 & \text{Unemployed, working age .} \\ \mathbf{p}_{it} & \text{if } j \geq 164 & \text{Retired} \end{cases}$$

A working-age household's employment state ℓ_{it} evolves as a Markov process described by the matrix Ξ , where element k, k' of Ξ is the probability of transitioning from $\ell_{it} = k$ to $\ell_{it+1} = k'$. During retirement, all households have $\ell_{it} = 0$ (or any other trivializing assumption about the "employment" state of the retired). We assume that households treat $\Xi_{0,2}$ and $\Xi_{1,2}$ as zero: they do not consider the possibility of ever attaining the deep unemployment state $\ell_{it} = 2$ from "normal" employment or unemployment, and thus it does not affect their consumption decision in those employment states.

We specify the unemployment rate during normal times as $\mathcal{U} = 5\%$, and the expected duration of an unemployment spell as 1.5 quarters. The probability of transitioning from unemployment back to employment is thus $\Xi_{1,0} = \frac{2}{3}$, and the probability of becoming unemployed is determined as the flow rate that offsets this to generate 5% unemployment (about 3.5%). The deeply unemployed expect to be unemployed for *much* longer: we specify $\Xi_{2,0} = 0$ and $\Xi_{2,1} = \frac{1}{3}$, so that a deeply unemployed person remains so for three quarters on average before becom-

¹⁵Unemployment is somewhat persistent in our model, so the utility risk from receiving 15% of permanent income for one quarter (as in Carroll, Slacalek, Tokunaka, and White (2017)) is roughly the same as the risk of receiving 30% of permanent income for 1.5 quarters in expectation.

ing “normal” unemployed (they cannot transition directly back to employment). Thus the unemployment spell for a deeply unemployed worker is 2 quarters at a minimum and 4.5 quarters on average.¹⁶

Like the prospect of deep unemployment, the possibility that consumption might become less appealing (via marginal utility scaling factor $\eta_{it} < 1$) does not affect the decision-making process of a household in the normal $\eta_{it} = 1$ state. If a household does find itself with $\eta_{it} = \underline{\eta}$, this condition is removed (returning to the normal state) with probability 0.5 each quarter; the evolution of the marginal utility scaling factor is represented by the Markov matrix H . In this way, the consequences of a pandemic are fully unanticipated by households, a so-called “MIT shock”; households act optimally once in these states, but did not account for them in their consumption–saving problem during “normal” times.¹⁷

The household’s permanent income level can be normalized out of the problem, dividing all boldface variables (absolute levels) by the individual’s permanent income \mathbf{p}_{it} , yielding non-bold normalized variables, e.g., $m_{it} = \mathbf{m}_{it}/\mathbf{p}_{it}$. Thus the only state variables that affect the choice of optimal consumption are normalized market resources m_{it} and the discrete Markov states n_{it} . After this normalization, the household consumption functions $c_{e,j}$ satisfy:

$$\begin{aligned} v_{e,j}(m_{it}, n_{it}) &= \max_{c_{e,j}} u(c_{e,j}(m_{it}, n_{it}), \eta_{it}) + \beta_i(1 - D_{e,j}) \mathbb{E}_t \left[\hat{\Gamma}_{it+1}^{1-\rho} v_{e,j+1}(m_{it+1}, n_{it+1}) \right] \\ &\text{s.t.} \\ a_{it} &= m_{it} - c_{e,j}(m_{it}, n_{it}), \\ m_{it+1} &= (R/\hat{\Gamma}_{it+1})a_{it} + y_{it}, \\ n_{it+1} &\sim (\Xi, H), \\ a_{it} &\geq 0, \end{aligned}$$

where $\hat{\Gamma}_{it+1} = \mathbf{p}_{it+1}/\mathbf{p}_{it}$, the realized growth rate of permanent income from period t to $t + 1$. Consumption function $c_{e,j}$ yields optimal *normalized* consumption, the ratio of consumption to the household’s permanent income level; the actual consumption level is simply $\mathbf{c}_{it} = \mathbf{p}_{it}c_{e,j}(m_{it}, n_{it})$.

Starting from the terminal model age of $j = 384$, representing being 120 years old (when the optimal choice is to consume all market resources, as death is certain), we solve the model by backward induction using the endogenous grid method, originally presented in Carroll (2006). Substituting the definition of next period’s market resources into the maximand, the household’s problem can be rewritten as:

$$v_{e,j}(m_{it}, n_{it}) = \max_{c_{it} \in \mathbb{R}_+} u(c_{it}, \eta_{it}) + \beta_i(1 - D_{e,j}) \mathbb{E}_t \left[\hat{\Gamma}_{it+1}^{1-\rho} v_{e,j+1}((R/\hat{\Gamma}_{it+1})a_{it} + y_{it}, n_{it+1}) \right]$$

¹⁶Our computational model allows for workers’ *beliefs* about the average duration of deep unemployment to differ from the *true* probability. However, we do not present results based on this feature and thus will not further clutter the notation by formalizing it here.

¹⁷Our computational model also allows households’ beliefs about the duration of the reduced marginal utility state (via social distancing) to deviate from the true probability. The code also permits the possibility that the reduction in marginal utility is lifted as an aggregate or shared outcome, rather than idiosyncratically. We do not present results utilizing these features here, but invite the reader to investigate their predicted consequences using our public repository.

$$\text{s.t. } a_{it} = m_{it} - c_{it}, \quad a_{it} \geq 0, \quad n_{it+1} \sim (\Xi, H).$$

This problem has one first order condition, which is both necessary and sufficient for optimality. It can be solved to yield optimal consumption as a function of (normalized) end-of-period assets and the Markov state:

$$\underbrace{\eta_{it} c_{it}^{-\rho}}_{=\frac{\partial u}{\partial c}} - \underbrace{\beta_i R(1 - D_{e,j}) \mathbb{E}_t \left[\widehat{\Gamma}_{it+1}^{-\rho} v_{e,j+1}^m ((R/\widehat{\Gamma}_{it+1})a_{it} + y_{it}, n_{it+1}) \right]}_{\equiv v_{e,j}^a(a_{it}, n_{it})} = 0 \implies c_{it} = \left(\frac{v_{e,j}^a(a_{it}, n_{it})}{\eta_{it}} \right)^{-\frac{1}{\rho}}.$$

To solve the age- j problem numerically, we specify an exogenous grid of end-of-period asset values $a \geq 0$, compute end-of-period marginal value of assets at each gridpoint (and each discrete Markov state), then calculate the unique (normalized) consumption that is consistent with ending the period with this quantity of assets while acting optimally. The beginning-of-period (normalized) market resources from which this consumption was taken is then simply $m_{it} = a_{it} + c_{it}$, the *endogenous gridpoint*. We then linearly interpolate on this set of market resources–consumption pairs, adding an additional bottom gridpoint at $(m_{it}, c_{it}) = (0, 0)$ to represent the liquidity-constrained portion of the consumption function $c_{e,j}(m_{it}, n_{it})$.

The standard envelope condition applies in this model, so that the marginal value of market resources equals the marginal utility of consumption when consuming optimally:

$$v_{e,j}^m(m_{it}, n_{it}) = \eta_{it} c_{e,j}(m_{it}, n_{it})^{-\rho}.$$

The marginal value function for age j can then be used to solve the age $j - 1$ problem, iterating backward until the initial age $j = 0$ problem has been solved.

When the pandemic strikes, we draw a new employment state (employed, unemployed, deeply unemployed) for each working age household using a logistic distribution. For each household i at $t = 0$ (the beginning of the pandemic and lockdown), we compute logistic weights for the employment states as:

$$\mathbb{P}_{i,\ell} = \alpha_{\ell,e} + \alpha_{\ell,p} \mathbf{p}_{i0} + \alpha_{\ell,j} j_{i0} \quad \text{for } \ell \in \{1, 2\}, \quad \mathbb{P}_{i,0} = 0,$$

where $e \in \{D, H, C\}$ for dropouts, high school graduates, and college graduates and j is the household's age. The probability that household i draws employment state $\ell \in \{0, 1, 2\}$ is then calculated as:

$$\Pr(\ell_{it} = \ell) = \exp(\mathbb{P}_{i,\ell}) / \sum_{k=0}^2 \exp(\mathbb{P}_{i,k}).$$

Our chosen logistic parameters are presented in Table A2.

B Aggregation

Households are modeled as individuals and incomes sized accordingly. We completely abstract from family dynamics. To get our aggregate predictions for income and consumption, we take the mean from our simulation and multiply by 253

million, the number of adults (over 18) in the United States in 2019. To size the unemployment benefits correctly, we multiply the benefits per worker by 0.8 to account for the fact that 20 percent of the working-age population is out of the labor force, so the average working-age household consists of 0.8 workers and 0.2 non-workers. With this adjustment, there are 151 million workers eligible for unemployment benefits in the model. Aggregate consumption in our baseline for 2020 is just over \$11 trillion, a little less than total personal consumption expenditure, accounting for the fact that some consumption does not fit in the usual budget constraint.¹⁸ Aggregating in this way underweights the young, as our model excludes those under the age of 24.

Our model estimates the aggregate size of the stimulus checks to be \$267 billion, matching the the Joint Committee on Taxation’s estimate of disbursements in 2020.¹⁹ This is somewhat of a coincidence: we overestimate the number of adults who will actually receive the stimulus, while excluding the \$500 payment to children.

The aggregate cost of the extra unemployment benefits depends on the expected level of unemployment. Our estimate is \$137 billion, much less than the \$260 billion mentioned in several press reports, but in line with the extent of unemployment in our pandemic scenario. We do not account for the extension of unemployment benefits to the self-employed and gig workers.

Households enter the model at age $j = 0$ with zero liquid assets. A ‘newborn’ household has its initial permanent income drawn lognormally with underlying standard deviation of 0.4 and an education-conditional mean. The initial employment state of households matches the steady state unemployment rate of 5%.²⁰

We assume annual population growth of 1%, so older simulated households are appropriately down-weighted when we aggregate idiosyncratic values. Likewise, each successive cohort is slightly more productive than the last, with aggregate productivity growing at a rate of 1% per year. The profile of average income by age in the population at any moment in time thus has more of an inverted-U shape than implied by the permanent income profiles from [Cagetti \(2003\)](#).

¹⁸PCE consumption in Q4 2019, from the NIPA tables, was \$14.8 trillion. Market based PCE, a measure that excludes expenditures without an observable price was \$12.9 trillion. Health care, much of which is paid by employers and not in the household’s budget constraint, was \$2.5 trillion.

¹⁹The JCT’s 26 March 2020 publication JCX-11-20 predicts disbursements of \$267 billion in 2020, followed by \$24 billion in 2021.

²⁰This is the case even during the pandemic and lockdown, so the death and replacement of simulated agents is a second order contribution to the profile of the unemployment rate.

Table A1 Parameter Values in the Baseline Model

Description	Parameter	Value
Coefficient of relative risk aversion	ρ	1
Mean discount factor, high school dropout	β_D	0.9637
Mean discount factor, high school graduate	β_{HS}	0.9705
Mean discount factor, college graduate	β_C	0.9756
Discount factor band (half width)	∇	0.0253
Employment transition probabilities:		
– from normal unemployment to employment	$\Xi_{1,0}$	2/3
– from deep unemployment to normal unemployment	$\Xi_{2,1}$	1/3
– from deep unemployment to employment	$\Xi_{2,0}$	0
Proportion of high school dropouts	θ_D	0.11
Proportion of high school graduates	θ_{HS}	0.55
Proportion of college graduates	θ_C	0.34
Average initial permanent income, dropout	\bar{p}_{D0}	5000
Average initial permanent income, high school	\bar{p}_{HS0}	7500
Average initial permanent income, college	\bar{p}_{C0}	12000
Steady state unemployment rate	\bar{U}	0.05
Unemployment insurance replacement rate	ξ	0.30
Skill rot of all unemployed	$\underline{\Gamma}$	0.995
Quarterly interest factor	R	1.01
Population growth factor	N	1.0025
Technological growth factor	\mathfrak{I}	1.0025

Table A2 Pandemic Assumptions

Description	Parameter	Value
Short-lived Pandemic		
Logistic parametrization of unemployment probabilities		
Constant for dropout, regular unemployment	$\alpha_{1,D}$	-1.15
Constant for dropout, deep unemployment	$\alpha_{2,D}$	-1.5
Constant for high school, regular unemployment	$\alpha_{1,H}$	-1.3
Constant for high school, deep unemployment	$\alpha_{2,H}$	-1.75
Constant for college, regular unemployment	$\alpha_{1,C}$	-1.65
Constant for college, deep unemployment	$\alpha_{2,C}$	-2.2
Coefficient on permanent income, regular unemployment	$\alpha_{1,p}$	-0.1
Coefficient on permanent income, deep unemployment	$\alpha_{2,p}$	-0.2
Coefficient on age, regular unemployment	$\alpha_{1,j}$	-0.01
Coefficient on age, deep unemployment	$\alpha_{2,j}$	-0.01
Marginal Utility Shock		
Pandemic utility factor	$\underline{\eta}$	0.891
Prob. exiting pandemic each quarter	$\bar{H}_{1,0}$	0.5
Long, Deep Pandemic		
Logistic parametrization of unemployment probabilities		
Constant for dropout, regular unemployment	$\alpha_{1,D}$	-1.45
Constant for dropout, deep unemployment	$\alpha_{2,D}$	-0.3
Constant for high school, regular unemployment	$\alpha_{1,H}$	-1.6
Constant for high school, deep unemployment	$\alpha_{2,H}$	-0.55
Constant for college, regular unemployment	$\alpha_{1,C}$	-1.95
Constant for college, deep unemployment	$\alpha_{2,C}$	-1.00
Coefficient on permanent income, regular unemployment	$\alpha_{1,p}$	-0.2
Coefficient on permanent income, deep unemployment	$\alpha_{2,p}$	-0.2
Coefficient on age, regular unemployment	$\alpha_{1,j}$	-0.01
Coefficient on age, deep unemployment	$\alpha_{2,j}$	-0.01
Marginal Utility Shock		
Pandemic utility factor	$\underline{\eta}$	0.891
Prob. exiting pandemic each quarter	$\bar{H}_{1,0}$	0.25

Table A3 Fiscal Stimulus Assumptions, CARES Act

Description	Value
Stimulus check	\$1,200
Means test start (annual)	\$75,000
Means test end (annual)	\$99,000
Stimulus check delay	1 quarter
Fraction that react on announcement	0.25
Extra unemployment benefit for:	
Normal unemployed	\$5,200
Deeply unemployed	\$7,800

Note: The unemployment benefits are multiplied by 0.8 to account for the fact that 20 percent of the working age population is out of the labor force. See aggregation details in Appendix B.