Pandemic Recession: L or V-Shaped?

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Abstract

We develop and calibrate a search-theoretic model of the labor market in order to forecast the evolution of the aggregate labor market during and after the coronavirus pandemic. The model is designed to capture the heterogeneity of the transitions of individual workers across states of unemployment, employment and across different employers. The model is also designed to capture the trade-offs in the choice between temporary and permanent layoffs. Under reasonable parametrizations of the model, the lockdown instituted to prevent the spread of the novel coronavirus is shown to have long-lasting negative effects on unemployment. This is so because the lockdown disproportionately disrupts the employment of workers who need years to find stable jobs.

JEL Codes: E24, O40, R11.

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1 Introduction

Since March 2020, the US has entered a lockdown in order to prevent the spread of the novel coronavirus. The vast majority of residents of the United States has been ordered to stay at home. Most retail businesses have been ordered to shut down. Most workers have been ordered to stay away from their place of work. Not surprisingly, during March and April of 2020, the number of claims for unemployment benefits has skyrocketed, exceeding on two months the total number of claims for during the entirety of the Great Recession. Is this enormous number of workers entering unemployment going to flow back into the ranks of the employed once the lockdown restrictions are lifted? Or are these workers going to remain unemployed long after the lockdown is gone? In this paper, we develop and quantify a framework to analyze and forecast the evolution of the labor market during and after the coronavirus pandemic. We find that, under reasonable parametrizations of the model, even a 3-month long lockdown is going to have long-lasting negative effects on unemployment.

Our framework is a search-theoretic model of the labor market in the spirit of Pissarides (1985) and Mortensen and Pissarides (1994). Workers endogenously transition across states of employment and unemployment, as well as from one employer to another. Workers search for jobs when they are unemployed. Workers search for more productive jobs when they are employed, albeit with a lower intensity. Workers move from employment into unemployment when their productivity falls below some threshold. If the productivity is low for transitory reasons, some workers and firms may suspend production but maintain (at some cost and imperfectly) the option of resuming it. As in Gregory, Menzio and Wiczer (2020), workers are ex-ante heterogeneous with respect to their baseline productivity, the distribution of the productivity that is idiosyncratic to their match with a particular employer, and with respect to their ability to search the labor market. The search process that brings workers and vacant jobs into contact is directed by wages, as in Moen (1997) and Menzio and Shi (2011).

According to our model, the lockdown—which we described as a temporary decline in labor productivity—causes some employment relationships to be terminated, some to be suspended, and others to continue. Intuitively, terminated relationships are those in which the surplus becomes negative because of the lockdown. Continuing and suspended relationships are those in which the surplus remains positive in spite of the lockdown. The difference between continuing and suspended relationships depends on whether the productivity is high enough to make it worthwhile to forego unemployment benefits in order to produce and maintain strong ties between the worker and the firm.

Once the lockdown is lifted, the speed of the recovery, depends on three factors: (i) the fraction of workers who, at the beginning of the lockdown, enter unemployment while maintaining a relationship with their employer; (ii) the rate at which inactive relationships dissolve during the lockdown; (iii) the rate at which workers who, at the end of the lockdown, are not recalled by their previous employer can find new, stable jobs. In turn, factors (i) and (ii) depend on the costs associated with maintaining and reactivating a temporarily inactive relationship, on the ability of the employer to survive the lockdown without revenues, and on the rate of decay in the quality of a temporarily inactive relationship. Factor (iii) depends on the job-finding rate of the non-randomly selected group of workers who are permanently laid off during the lockdown.

Depending on parameters, the model can generate either a V-shaped recession—one in which the unemployment rate quickly returns to its baseline level once the lockdown restrictions are lifted—or an L-shaped recession—one in which the unemployment rate takes several years to return to its pre-lockdown level. As a matter of theory, a V-shaped recession occurs if: (a) workers who enter unemployment are in a suspended relationship with their previous employer and maintain it throughout the lockdown; or (b) workers who, by the end of the lock down, have no relationship to their previous employer can quickly find a new, stable job. In contrast, an L-shaped recession occurs if: (a) a sizeable fraction of workers who flow into unemployment do not maintain ties to their previous employer; and (b) they cannot find quickly a new, stable job.

We calibrate the model using data from the Longitudinal Employer and Household Dynamics (LEHD) and the Survey of Income and Program Participation (SIPP) to capture three features of the labor market: (i) the fact that workers differ systematically with respect to the duration of their unemployment spells, and with respect to the tenure length of their jobs; (ii) the prevalence of different types of workers in different industries; (iii) the increase in unemployment across industries in March and April 2020. We find 3 distinct types of workers. At one extreme, there are ”stable” workers with high productivity, short unemployment spells, and a high probability of staying on a job for more than 2 years. At the other extreme, there are ”fickle” workers with low productivity, long unemployment spells, and a low probability of staying on a job for more than 2 years. We find that the prevalence of “fickle” workers varies a lot across industries and happens to be high in some of the industries hit hardest by the lockdown.

Using the calibrated framework, we measure the shape of the pandemic recession. We model the recession as 3-months lockdown—which affects differently the productivity of workers in different industries—followed by a 12-month period of uncertainty—during which productivity is back to normal but there is a risk of a second lockdown. Throughout the lockdown and uncertainty phase, unemployment benefits are augmented by special federal programs. We find that the recession has an L-shape. The finding is easy to explain. First, even when the cost of maintaining and reactivating a suspended employment relationship is fairly small—in the order of less than a month of the worker’s value added—the fraction of workers whose employment relationship is permanently terminated is about 35%. This is consistent with survey evidence, which finds that between 40 and 50% of the workers who have entered unemployment during the first month of the lockdown have no expectation of being recalled to their previous job (see, Adams-Prassl et al. 2020 and Bick and Blandin 2020). Second, the workers who are permanently laid-off are disproportionately of the ”fickle” type, who need to search for several years in order to find a long-lasting job. Interestingly, increasing the length of the lockdown from 3 to 6 months does not significantly affect the behavior of unemployment 4 years out.

We believe that our simulation represents a lower bound on the effect of the pandemic on unemployment. Indeed, we abstract from several important channels that are likely to slow down the recovery of unemployment. First, it is unlikely that the lockdown will be entirely lifted after 3 months and that, once lifted, productivity will immediately return to its normal level. Second, even employment relationships that are kept active throughout the lockdown are likely to break down at a rate higher than normal due to bankruptcies. Third, contractual frictions may cause some viable employment relationships to break down during the lockdown. A leading example of contractual frictions are rigid wages (see, e.g., Hall 2005, Gertler and Trigari 2009, or Menzio and Moen 2010), minimum wages, or costs to renegotiate contracts in the face of unforeseen contingencies.

The paper contributes to recent work on the economic consequences of the pandemic. A non-exhaustive list of this line of work is Alvarez, Argente and Lippi (2020), Atkeson (2020), Berger, Herkenhoff and Mongey (2020), Eichenbaum, Rebelo and Tradandt (2020), Glover et al. (2020), Guerrieri et al. (2020), Kapicka and Rupert (2020), Kaplan, Moll and Violante (2020), Jones, Philippon and Venkateswaran (2020). Compared with this literature, the focus of our paper is on forecasting the aggregate dynamics of the labor market starting from the disaggregate and heterogeneous dynamics of individual workers. Compared with this literature, we are also silent about optimal policy. We believe that a calculation of the "optimal unemployment rate" during a pandemic would require calculations that are surely important but that fall outside of the scope of our expertise.

2 Environment and Equilibrium

In this section, we present our model of the labor market. The basic structure of the model is the same as in Menzio and Shi (2010, 2011). Firms and workers come together in the labor market through a search process directed by the terms of employment contracts. Firms search the market by posting employment contracts for their vacancies. Workers search the market by seeking vacancies offering the desired employment contract. Matches between firms and workers are heterogeneous with respect to their quality, which gives employed workers a motive for searching not only off but also on the job. We add two new ingredients to this basic structure. First, we allow for the possibility that workers are ex-ante heterogeneous. In particular, different types of workers are heterogeneous with respect to their productivity, the distribution of match quality from which they sample, and their ability to search. As documented in Ahn and Hamilton (2019), Morchio (2020), Kudlyak and Hall (2019) and Gregory, Menzio and Wiczer (2020), there are systematic differences across workers in their UE (unemployment to employment), EU (employment to unemployment) and EE (employer to employer) rates. Second, we allow for the possibility that workers and firms might temporarily deactivate their match, while retaining the option of resuming production at a later date. As documented in Fujita and Moscarini (2017), workers frequently return to their previous job after a spell of unemployment. As we shall see, these two new ingredients are critical to understand the aggregate dynamics of the labor market.

2.1 Environment

The labor market is populated by a positive measure of workers and firms. Workers are ex-ante heterogeneous with respect to their type $i = 1, 2, ...I$, which affects their productivity, unemployment income, and their search and learning processes. A worker of type i maximizes the present value of income, discounted at the factor $\beta \in (0, 1)$. A worker of type i earns some income b_i when he is unemployed, and some income w_i when he is employed. The unemployment income b_i is a combination of unemployment benefits, transfers, and income value of leisure. The employment income w_i is determined by the worker's employment contract. The measure of workers of type i is $\mu_i \geq 0$ and the total measure of workers is 1.

Firms are ex-ante homogeneous. A firm maximizes the present value of profits, discounted at the factor β. A firm operates a constant returns to scale technology which turns the labor supply of a worker of type i into $y_i z$ units of output, where y_i is a component that is common to all pairs of firms and workers of type

i, and $z \in Z$ is a component that is specific to a particular firm-worker pair. The first component is the source of persistent differences in the productivity of different types of workers. The second component is the source of worker's job mobility. We refer to the second component of productivity as the quality of a firm-worker match.

The labor market is organized in a continuum of submarkets indexed by the vector $x = \{v, i\}$, where $v \in R$ denotes the lifetime utility promised by firms to workers hired in submarket x, and $i \in \{1, 2, ...I\}$ denotes the type of workers hired by firms in submarket x.[1] Associated with each submarket, there is an endogenous vacancy-to-applicant ratio $\theta_i(v) \in \mathbb{R}_+$. If a worker searches in submarket $x = \{v, i\}$, he finds a vacancy with probability $p(\theta_i(v))$, where p is a strictly increasing, strictly concave function with $p(0) = 0$ and $p(\infty) = 1$. A vacancy in submarket $x = \{v, i\}$ meets an applicant with probability $q(\theta_i(v))$, where q is a strictly decreasing function with $q(\theta) = p(\theta)/\theta$, $q(0) = 1$ and $q(\infty) = 0$.

The state of the economy is described by some exogenous state $s \in S$ and by the endogenous distribution of workers across employment states. The exogenous state s evolves stochastically, and its realization may affects the type-specific productivity y_i and the type-specific unemployment income b_i. To understand the endogenous distribution of workers across employment states, note that a worker may be unemployed without the option to recall its old job, unemployed with the option to recall a match of unknown quality, unemployed with the option to recall a match of known quality, employed in a match of unknown quality, or employed in a match of known quality. Let u_i be the measure of unemployed workers without the option to recall their old job, m_i the measure of unemployed workers with the option to recall a job with unknown quality. $q_i(z)$ the measure of unemployed workers with the option to recall a job with known quality z, n_i the measure of employed workers in a match of uknown quality, and $g_i(z)$ the measure of employed workers in a match of known quality z. Overall, the state of the economy is described by $\psi \equiv \{s, u_i, m_i, q_i, n_i, g_i\}$.

Every period comprises six stages: learning, separation, recall, search, matching and production. In the first stage, a worker of type i who is employed in a match with an unknown idiosyncratic component of productivity discovers the quality of the match with probability $\phi_i \in [0, 1]$. The idiosyncratic component of productivity z is a random draw from a probability density function $f_i : Z \to \mathbb{R}_+$ with a mean normalized to 1.

In the second stage, an employed worker of type i becomes unemployed with probability $d_e \in [\delta, 1]$. The probability d_e is specified by the worker's employment contract. The lower bound δ represents the probability that the worker has to leave the match for exogenous reasons (e.g., worker relocation). Similarly, an unemployed worker with a recall option loses contact from his old employer with probability $d_q \in [\delta_q, 1]$, where d_q is specified by the worker's employment contract. The lower bound δ_q represents the probability that the worker and the firm lose contact for exogenous reasons (e.g., firm bankruptcy).

In the third stage, an employed worker of type i becomes unemployed with a recall option with probability $\ell \in [0, 1]$, where ℓ is specified by the worker's contract. Similarly, an unemployed worker with a recall option returns to his old job with probability $h \in [0, 1]$, where again h is a prescription of the employment

[1]Second, we assume that a worker knows his own type and so does the market. The second part of the assumption may appear unrealistic to some readers, but it does greatly simplify the model. In particular, the assumption allows us to abstract from issues of signaling—the worker distorting his behavior so as to convince the market that his type is better than what it actually is—as well as from issues of inference—the firms trying to assess the probability distribution of a worker's type by examining his employment history and performance on the job.

contract. When a worker recalls his old job, he and his employer have to pay a fixed cost $C_i \geq 0$, which captures the legal and technical costs of resuming production.

In the fourth stage, a worker gets the opportunity to search the labor market with a probability that depends on his type and on his employment status. If a worker of type i is unemployed without a recall option, he gets to search with probability $\lambda_u^i \in [0, 1]$. If the worker is unemployed with a recall option, he gets to search with probability $\lambda_q^i \in [0, \lambda_u^i]$. If the worker is employed, he gets to search with probability $\lambda_e^i \in [0, \lambda_u^i]$. Whenever the worker gets to search, he chooses which submarket x to visit. In the same stage, firms choose how many vacancies to open in submarket $x = \{v, i\}$ at the unit cost $k_i > 0$.

In the fifth stage, workers and firms searching in submarket $x = \{v, i\}$ meet bilaterally. When a firm and a worker of type i meet in submarket x, the firm offers to the worker an employment contract that is worth v in lifetime utility. If the worker accepts the offer, he becomes employed by the firm under the rules of the contract. If the worker rejects the offer–which is an off-equilibrium event–he returns to his previous employment status. When a firm and a worker of type different from i meet in submarket x, the firm does not offer an employment contract to the worker.

In the last stage, an unemployed worker without a recall option enjoys an income of b_i units of output. An unemployed worker with a recall option enjoys an income of b_i units of output, while the worker's old employer pays a cost c_i to maintain the recall option alive. A worker of type i employed in a match of unknown quality produces, in expectation, y_i units of output. A worker of type i employed in a match of known quality z produces $y_i z$ units of output. The worker's consumption is w_i, which is determined by the employment contract. After production and consumption take place, next period's state, $\hat{s}$, is drawn from the probability density function $h : S \times S \rightarrow \mathbb{R}_+$ with $h(\hat{s}, s)$ denoting the probability density of $\hat{s}$ conditional on s.

We assume that employment contracts maximize the joint value of a firm-worker match, i.e. the sum of the worker's lifetime utility and the firm's present value of profits generated by the worker. We also assume that the domain of the employment contract includes not only the employment relationship proper, but also the time during which a worker is unemployed with the option of reactivating the relationship. As discussed in Menzio and Shi (2011), there are many contractual environments with the property that the contract that maximizes the profit of the firm subject to providing the worker any given lifetime utility also maximizes the joint value of the match. We abstract from contractual incompleteness caused by either wage rigities or missing contingencies.

2.2 Equilibrium

To define equilibrium, we need to introduce some additional pieces of notation. Let $U_i(\psi)$ denote the value of unemployment without recall for a worker of type i. Let $\tilde{Q}_i(\psi)$ denote the joint value to the worker and the firm from a temporarily inactive match (i.e. the worker is unemployed with the option to recall). Similarly, $Q_i(z, \psi)$ denotes the joint value to the worker and the firm from a temporarily inactive match of known quality z. Lastly, Let $\tilde{V}_i(\psi)$ and $V_i(z, \psi)$ denote, respectively, the joint value of an active match of unknown quality and quality z. All value functions are evaluated at the beginning of the production stage.

In what follows, we will suppress the dependece of the value functions from i and ψ in order to keep the notation light. The value for an unemployed worker without a recall option is

$$U = b(s) + \beta E_{\hat{\psi}} \left\{ U + \lambda_u^i \max_v \{ p(\theta(v))(v - U) \} \right\}. \tag{1}$$

In the current period, the worker's income is $b(s)$. In the next period, the worker gets an opportunity to search with probability λ_u. If the worker searches in submarket v, he meets a firm with probability $p(\theta(v))$, in which case his continuation lifetime utility is v. If the worker does not get the opportunity to search, or if the search is unsuccessful, his continuation value is U.

The joint value of an active match of quality z between a worker and a firm is

$$\begin{aligned} &V(z) = y(s)z + \\ &\beta E_{\hat{\psi}} \left\{ \max_d \left\{ dU + (1-d) \max_\ell \left\{ \ell Q(z) + (1-\ell) \left[V(z) + \lambda_e \max_v p(\theta(v))(v - V(z)) \right] \right\} \right\} \right\} \end{aligned} \tag{2}$$

In the current period, the sum of the worker's income and firm's profit is $y(s)z$. In the next separation stage, the worker moves into unemployment with probability d. In this case, the worker's continuation value is U and the firm's continuation profit is zero. In the next recall stage, the worker and the firm deactivate the match with probability ℓ, in which case their joint continuation value is $Q(z)$. The worker and the firm keep the match active with probability $1-\ell$. In this case, the worker gets an opportunity to search with probability λ_e. If the worker searches in submarket v, he meets a new employer with probability $p(\theta(v))$. In this case, the worker's continuation value is v and the firm's continuation value is 0. If the worker does not get to search or if the search is unsuccessful, the joint continuation value is $V(z)$. Note that, since employment contracts are bilaterally efficient, d, ℓ and v are chosen so as to maximize the joint value of the match.

The joint value of an active match of unknown quality is

$$\begin{aligned} &\tilde{V} = y(s) \\ &+\beta(1-\phi) E_{\hat{\psi}} \left\{ \max_d \left\{ dU + (1-d) \max_\ell \{ \ell \tilde{Q} + (1-\ell) \left[\tilde{V} + \lambda_e \max_v \left\{ p(\theta(v)) \left(v - \tilde{V} \right) \right\} \right] \right\} \right\} \\ &+\beta\phi E_{\hat{\psi}} \left\{ \sum_z f(z) \max_d \left\{ dU + (1-d) \max_\ell \{ \ell Q(z) + (1-\ell) \left[V(z) + \lambda_e \max_v \{ p(\theta(v)) (v - V(z)) \} \right] \right\} \right\}. \end{aligned} \tag{3}$$

In the current period, the joint income of the match is $y(s)$ (in expectation). With probability $1-\phi$, the firm and the worker do not discover the quality of the match. With probability ϕ, the firm and the worker discover the quality z of the match, where z is drawn from the f distribution. Conditional on discovering or nor discovering the match quality, the firm and the worker choose d, ℓ and v to maximize the joint value.

The joint value of a temporarily inactive match of quality z between a worker and a firm is

$$\begin{aligned} &Q(z) = b(s) - c + \\ &\beta E_{\hat{\psi}} \left\{ \max_d \left\{ dU + (1-d) \max_h \left\{ h \left[V(z) - c \right] + (1-h) \left[Q(z) + \lambda_q \max_v p(\theta(v))(v - Q(z)) \right] \right\} \right\} \right\} \end{aligned} \tag{4}$$

In the current period, the sum of the worker's income and firm's profit is $b(s) - c$. In the next separation stage, the worker moves into permanent unemployment with probability d. In this case, the worker's continuation value is U and the firm's continuation profit is zero. If the next recall stage, the worker and the firm reactivate the match with probability h, in which case their joint continuation value is $V(z) - c$. The worker and the firm keep the match inactive with probability $1 - h$. In this case, the worker gets an opportunity to search with probability λ_q. If the worker searches in submarket v, he meets a new employer with probability $p(\theta(v))$. In this case, the worker's continuation value is v and the firm's continuation value is 0. If the worker does not get to search or if the search is unsuccessful, the joint continuation value is $Q(z)$.

The joint value of a temporarily inactive match of unknown quality is

$$\begin{aligned} \tilde{Q} &= b(s) - c + \\ &\beta E_{\hat{\psi}} \left\{ \max_d \left\{ dU + (1-d) \max_h \left\{ h \left[\tilde{V} - c \right] + (1-h) \left[\tilde{Q} + \lambda_q \max_v p(\theta(v))(v - \tilde{Q}) \right] \right\} \right\} \right\} \end{aligned} \tag{5}$$

The expression above is analogous to (4) and requires no comment.

The tightness $\theta(v)$ of submarket v is such that

$$k \geq q(\theta(v)) \left[\tilde{V} - v \right], \tag{6}$$

and $\theta(v) \geq 0$, with the two inequalities holding with complementary slackness. The left-hand side of (6) is the cost to a firm from opening a vacancy in submarket v. The right-hand side is the benefit to the firm from opening a vacancy in submarket v. The benefit is the probability that the firm fills its vacancy, $q(\theta(v))$, times the firm's value from filling a vacancy, $\tilde{V} - v$, i.e. the joint value of a match between the firm and a worker net of the lifetime utility promised by the firm to the worker.

We can easily characterize the solution of the search problems in (1)-(5). These problems have the common structure

$$\max_v p(\theta(v))(v - r), \tag{7}$$

where r denotes the value of the worker's current employment status. For any v such that $\theta(v) > 0$, (6) implies that v is equal to $-k\theta(v) + p(\theta(v))\tilde{V}$. For any v such that $\theta(v) = 0$, $p(\theta(v))$ is equal to zero. From these observations, it follows that (7) can be written as

$$\max_v -k\theta(v) + p(\theta(v))(\tilde{V} - r). \tag{8}$$

Now, notice that, for all $\theta \geq 0$, there exists a v such that $\theta(v) = \theta$. Thus, by changing the choice variable from v to θ in (8), we do not enlarge the choice set. Conversely, for all v, there exists a $\theta \geq 0$ such that $\theta = \theta(v)$. Thus, by changing the choice variable from v to θ in (8), we do not shrink the choice set. From these observations, it follows that (8) can be written as

$$\max_{\theta \geq 0} -k\theta + p(\theta)(\tilde{V} - r). \tag{9}$$

From the above formulation, it follows immediately that a worker employed in a match of unknown quality has no reason to actively search.

To formulate the laws of motion for the distribution of workers across employment states, we need some notation describing the policy functions. We denote as $d_e(z)$ and $d_q(z)$ the optimal probability that a worker employed in an active or inactive match of quality z moves into unemployment. We denote as $d_e(\emptyset)$ and $d_q(\emptyset)$ denote that probability for a worker employed in an active or inactive match of uknown quality. We denote as $\ell(z)$ and $\ell(\emptyset)$ the optimal probability that an active match of known or unknown quality becomes inactive. We denote as $h(z)$ and $h(\emptyset)$ the optimal probability that an inactive match of known or unknown quality becomes active. We denote as θ_u, $\theta_q(z)$, $\theta_e(z)$ the optimal search strategy for an unemployed worker without a recall option, an unemployed worker with an option to recall a match of quality z, and an employed worker in a match of quality z.

The law of motion for the measure of unemployed workers without recall is

$$\begin{aligned}\hat{u} = u(1-\lambda_u p(\theta_u)) + \textstyle\sum_z d_e(z)\left[g(z) + n\phi f(z)\right] \\ + \textstyle\sum_z d_q(z) q(z) + n(1-\phi) d_e(\emptyset) + m d_q(\emptyset)\end{aligned} \tag{10}$$

The law of motion for the measure of workers employed in an active match of uknown quality is

$$\begin{aligned}\hat{n} = u\lambda_u p(\theta_u) &+ \textstyle\sum_z (1-d_e(z))(1-\ell(z))\lambda_e p(\theta_e(z))\left[g(z) + n\phi f(z)\right] \\ &+ \textstyle\sum_z (1-d_q(z))(1-h(z))\lambda_q p(\theta_q(z)) q(z) \\ &+ n(1-\phi)(1-d_e(\emptyset))(1-\ell(\emptyset)) \\ &+ m(1-d_q(\emptyset))\left[h(\emptyset) + (1-h(\emptyset))\lambda_q p(\theta_q(\emptyset))\right]\end{aligned} \tag{11}$$

The law of motion for the measure of workers employed in an active match of known quality z is

$$\begin{aligned}\hat{g}(z) = \left[g(z) + n\phi f(z)\right](1-d_e(z))(1-\ell(z))(1-\lambda_e p(\theta_e(z))) \\ + q(z)(1-d_q(z))h(z)\end{aligned} \tag{12}$$

The law of motion for the measure of unemployed workers with the option to recall a match of quality z is

$$\begin{aligned}\hat{q}(z) = q(z)(1-d_q(z))(1-h(z))(1-\lambda_q p(\theta_q(z))) \\ + \left[g(z) + n\phi f(z)\right](1-d_e(z))\ell(z)\end{aligned} \tag{13}$$

Lastly, the law of motion for the measure of unemployed workers with the option to recall a match of unknown quality is

$$\begin{aligned}\hat{m} = m(1-d_q(\emptyset))(1-h(\emptyset))(1-\lambda_q p(\theta_q(\emptyset))) \\ + n(1-\phi)(1-d_e(\emptyset))\ell(\emptyset)\end{aligned} \tag{14}$$

All of the above expressions are easy to understand.

A Recursive Equilibrium (RE) is such that: (i) the value functions $\{U, \tilde{V}, V, \tilde{Q}, Q\}$ satisfy the Bellman Equations (1)-(5); (ii) the policy functions $\{d_e, d_q, \theta_u, \theta_e, \theta_q, \ell, h\}$ satisfy the optimality conditions in (1)-(5); the distribution of workers across employment states $\{u, m, n, q, g\}$ follows the laws of motion (10)-(14). A Block Recursive Equilibrium (BRE) is a RE such that the value and policy functions depends on the aggregate state of the economy ψ only through the exogenous state s, and not through the endogenous distribution of workers across employment states. A Block Recursive Equilibrium is much easier to solve, as it requires solving a system of functional equations with the one-dimensional state s as an aggregate

Parameter	Value	Description
β	0.996	discount factor
b_i	(0.661, 0.563, 0.458)	flow unemployment income
y_i	(1, 0.623, 0.459)	type-specific productivity
α_i	(4, 4, 1)	shape of f_i
σ_i	(0.117, 0.203, 0.08)	standard deviation of f_i
ϕ_i	(0.25, 0.225, 0.25)	probability match quality is discovered
λ_e^i	(0.344, 0.763, 0.70)	probability an employed worker searches
λ_u^i, λ_q^i	1	probability an unemployed worker searches
k_i	(12.54, 25.92, 5.37)	vacancy posting cost
γ	0.5	elasticity of job-finding rate wrt tightness
δ	0.005	exogenous separation probability
δ_q	0.10	probability recall option is lost
c_i	(0.05, 0.031, 0.023)	cost of maintaining recall option
C_i	(0.25, 0.156, 0.115)	cost of reactivating a match

Table 1: Model Parameters

state variable. As proved in Menzio and Shi (2011) in the context of a similar model, there exists a BRE, the BRE is unique, and there exists no other equilibrium that is not block-recursive.

3 Calibration

Using data from the Longitudinal Employer and Household Dynamics (LEHD) over the period 1997-2014, we apply a k-mean algorithm to group workers based on to their similarity with respect to the frequency and duration of unemployment spells and the number and length of jobs.[2] The algorithm identifies 3 types of workers, which we shall refer to as α, β and γ. About 55% of workers are of type α. For a worker of type α, the duration of a job is less than a year with probability 30%, and more than 2 years with probability 50%. For a worker of type α, unemployment spells are short. About 25% of workers are of type β. For a worker of type β, the duration of a job is less than a year with probability 40%, and more than 2 years with probability 40%. For a worker of type β, unemployment spells are longer than for α-workers. About 20% of the workers are of type γ. For a worker of type γ, the duration of a job is less than a year with probability 65%, and more than 2 years with probability 15%. These workers have the longest duration of unemployment. Workers of different types also have different average earnings. Specifically, the average earnings for β-workers are 70% compared to the average earnings for α-workers. The average earnings for γ-workers are about 50% compared to the earnings for α-workers. The worker type characteristics described above are the key calibration targets[3]

[2]In the LEHD, we cannot distinguish between unemployment and non-employment. We identify unemployment as a spell without earnings that lasts less than 2 years. In the LEHD, we only have quarterly observations and, thus, we cannot directly measure short unemployment spells. We impute am unemployment spells between two jobs by comparing earnings in the first job and earnings in the second job. If, during the transition from the first to the second job, there is a quarter in which earnings are lower than the minimum of the typical earnings in the two jobs, we impute an unemployment spell.

[3]Details about the calibration algorithm are available upon request.

Let us review the parameters that describe the non-stochastic steady state of the model. These parameters are summarized in Table 1. Preferences are described by the discount factor, β, and by the flow unemployment income, b_i. Production is described by the type-specific component of productivity, y_i, and by the distribution of the match-specific component of productivity, f_i. We specialize the distribution f_i to be a Weibull distribution with shape α_i and scale σ_i, shifted to have a mean of 1. Learning is described by the probability ϕ_i with which a worker and a firm discover the component of productivity that is idiosyncratic to their match.

Search is described by the probability that a worker can search the labor market when unemployed without a recall option, λ_u^i and when employed, λ_e^i. Further, search depends on the vacancy cost, k_i, and on the job-finding probability function, $p(\theta)$. We normalize λ_u^i to 1. We specialize $p(\theta)$ to have the form $\min\{\theta^\gamma, 1\}$, where γ is the elasticity of the job-finding probability with respect to tightness.

The recall process is characterized by the parameters λ_q, the probability that an unemployed worker with a recall option can search the labor market, δ_q, the probability that an unemployed worker loses his recall option, and by c_i and C_i, the flow cost of maintaining the recall option and the fixed cost of exercising the recall option. None of these parameters affect the non-stochastic steady-state, because absent aggregate shocks, there are no firm-worker matches that are temporarily inactive. We shall discuss our choice of the parameters describing the recall process in a few pages.

Now, let us describe our calibration strategy in broad strokes. We use the empirical duration of unemployment spells to calibrate k_i. We use the empirical distribution of job durations to calibrate α_i, σ_i and ϕ_i. We normalize $y_\alpha = 1$ and choose y_β and y_γ to match the difference in avearge earning between different types of workers. As suggested by Hagedorn and Manovskii (2008) and Hall and Milgrom (2009), the proper interpretation of b_i is the sum of an unemployment benefit, ζ_i, and the income value of leisure, ℓ. We choose the unemployment benefit for workers of type i to be equal to 40% of the average labor income for workers of type i, which is the typical replacement rate of unemployment insurance in the US. We choose the value of leisure, ℓ, so that, in the average of the whole population of workers, the flow value of unemployment is equal to 65% of labor income, a percentage that Hall and Milgrom (2008) argue is sensible for the US economy. We tentatively set δ to 0.5% per month. We tentatively set γ to 0.5. Neither of these parameters has much of an effect on our simulation results.

4 Simulating the Pandemic Recession

To describe and simulate the pandemic recession, we stratify the model by 2-digit industry. Using data from the Survey of Income and Program Participation (SIPP), we compute the distribution of job durations industry by industry. We choose the fraction of workers of type α, β and γ in industry j to minimize the distance between the distribution of job durations in industry j in the data and in the model. We carry out the minimization subject to a constraint requiring that the sum of workers of type α, β and γ across all industries is equal with the fraction of workers of type α, β and γ in the LEHD. Figure 1 shows the distribution of types by industry.

To describe the pandemic recession, we assume that the economy can be in one of three states: lockdown (s_L), uncertainty (s_U), or recovery (s_R). Intuitively, the lockdown state is meant to capture the current

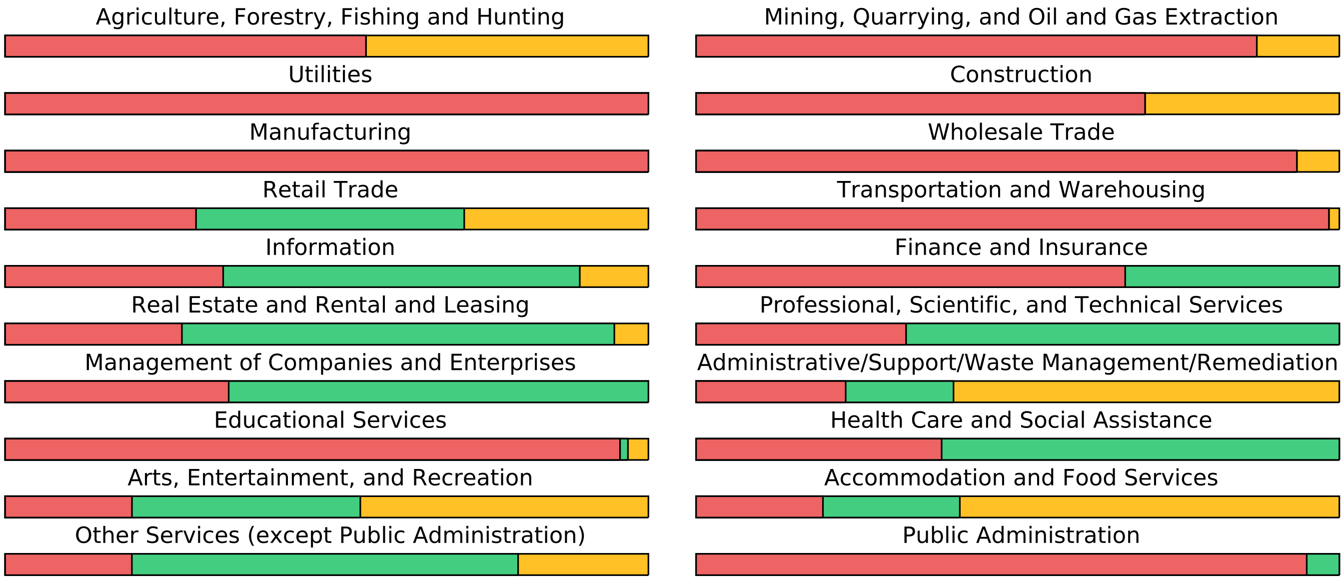

Figure 1: Proportion of workers of type α (pink), β (green), and γ (yellow)

phase of severe restrictions on economic activity. The uncertainty state is meant to capture a phase in which restrictions on economic activities are lifted, but there is a risk of a return to the lockdown state (because of, say, a second wave of infections). The recovery state is meant to capture the return to normalcy (because of, say, an effective vaccine is discovered). The three states differ with respect to productivity and unemployment income. In the lockdown state, the productivity y_i of i-workers employed in industry j is multiplied by some factor $A_{L,j}$, which is typically smaller than 1 and captures the (industry-specific) effect of restrictions on economic activity. The unemployment income is multiplied by some factor $B_L > 1$, which captures the increase in unemployment benefits granted by the CARES Act. In the uncertainty state, the productivity of i-workers employed in industry j returns to its normal value, i.e. $A_{U,j} = 1$. The unemployment income, however, is still multiplied by some factor $B_U > 1$ to capture the idea that the increase in the generosity of unemployment benefits may outlast the lockdown. In the recovery state, both productivity and unemployment income return to their normal values, i.e. $A_{R,j} = 1$ and $B_R = 1$. When the aggregate state is s_L, the probability of moving to s_U is 75% per month and the probability of moving to s_R is zero. When the aggregate state is s_U, the probability of returning to s_L is 13% per month, and the probability of moving to s_R is 6.5%. The s_R state is absorbing.

There are several parameters that have yet to be chosen in order to simulate the recession. We calibrate the vector of productivity shocks $A_{L,j}$ so that: (a) the aggregate unemployment rate increases by 19 percentage points during the lockdown—which we take it to be a sensible guess based on the number of unemployment insurance claims during March and April 2020; and (b) the relative increase in the unemployment rate across industries matches the relative flow of new unemployment claims across industry—which we measure for the states of Washington, Texas, Ohio and Nebraska. We set the unemployment income shock B_L to 1.3 or, equivalently, $1,000$ US\$ per month. This is less than what offered by the CARES act because we want to capture, albeit crudely, the fact that not all unemployed workers will be awarded the additional benefits. In the baseline, we set B_U to 1.3, but we present results for other values as well.

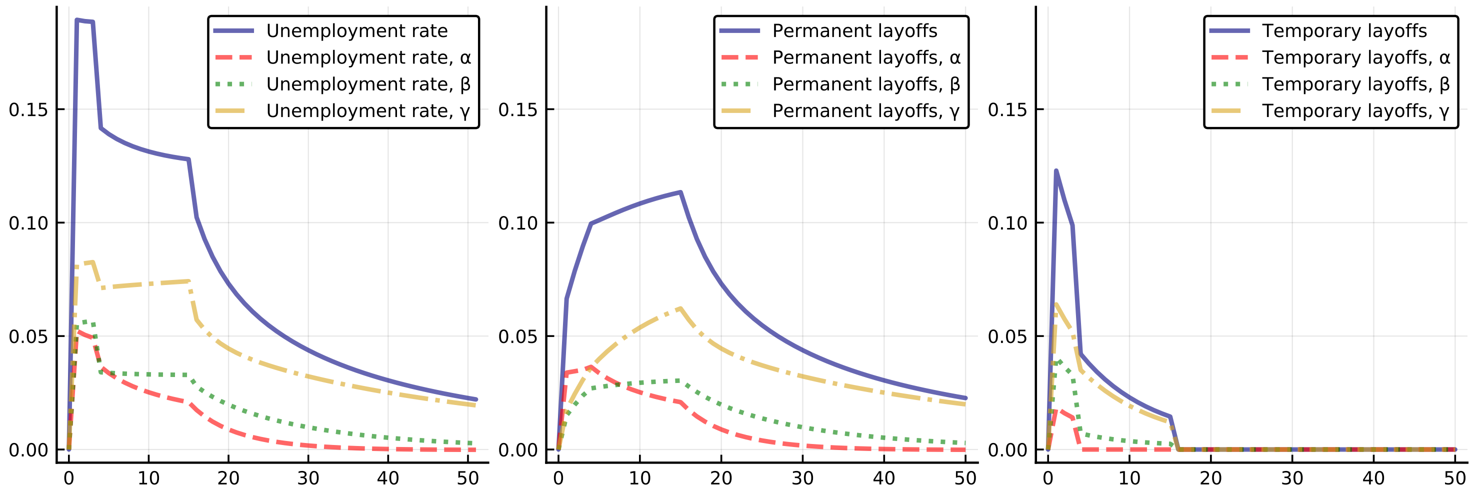

Figure 2: Baseline simulation of pandemic

The parameters describing the process of recall require some guesswork. We assume that unemployed workers with the option to recall their old job have the same probability of searching the labor market as unemployed workers without such an option, i.e. $\lambda_q^i = \lambda_u^i$. We assume that the rate at which a firm-worker match exogenously breaks down when it is temporarily inactive is 10% per month, i.e. $\delta_q = 0.1$. The particular values chosen for λ_q and δ_q do not have a significant impact on the simulation of the pandemic. In contrast, the cost of maintaining the option of recall, c_i, and the cost of exercising the recall option, C_i, play an important role. Intuitively, both costs affect the trade-off between permanently terminating or temporarily deactivating a firm-worker match when its productivity is depressed by the lockdown. The relative magnitude of the two costs affects the trade-off between recalling a temporarily deactivated match as soon as the lockdown is lifted or only when the risk of a lockdown is eliminated. Indeed, if $C_i = 0$, the match can be activated and deactivated at no cost and, thus, the decision will be essentially determined by a static comparison between $b(s) - c$ and $y(s)z$. If, in contrast, $C_i > 0$, the firm and the worker are discouraged from deactivating and reactivating their match often.

Figure 2 illustrates the simulation of the pandemic recession under our baseline calibration. For the purposes of the simulation, we assume that the economy is in the lockdown state for 3 months, in the uncertainty state for 12 months, and in the recovery state afterwards. Panel (a) plots the unemployment rate, measured in deviation from the steady-state. Panel (b) plots the fraction of workers who are unemployed without a recall option (permanently laid-off), measured in deviation from the steady state. Panel (c) plots the fraction of workers who are unemployed with a recall option (temporarily laid-off), measured in deviation from the steady state. The dashed lines in the three panels show the decomposition of the aggregates by type of worker.

As the economy enters the lockdown, the unemployment rate increases by 19 percentage points. About 13 percentage points of the increase are due to temporary separations between workers and firms, the remaining 6 percentage points are due to permanent separations. As the economy exits the lockdown, approximately half of the workers on temporary layoff are recalled by their previous employer. Moreover, the UE rate increases and the unemployed workers on permanent layoff start flowing back into employment. Overall, during the 12 months between the exit from the lockdown state and the entry into the recovery state, the unemployment rate falls by about 5 percentage points. As the economy enters the recovery state, all remaining workers on temporary layoffs are recalled. Moreover, the UE rate returns to its pre-lockdown level. Thus, the unemployment rate starts its descent towards its old steady-state level.

Even though the lockdown lasts for as little as 3 months, the unemployment rate is still about 5 percentage points above its steady-state level 30 months after the beginning of the pandemic. Similarly, the unemployment rate is still about 2.5 percentage points above its steady-state level 50 months after the beginning of the pandemic. A recession with this kind of slow recovery is sometimes dubbed an "L-shaped" recession. The slow pace of the recovery is caused by the ex-ante heterogeneity of workers. As can be seen from Panel (a), the excess unemployment for α-workers subsides fairly quickly. This is because α-workers have a high UE rate and, once they find a job, they are likely to keep it for a long time. The excess unemployment for the γ-workers, however, subsides much more slowly and, eventually, it causes the recovery of aggregate unemployment to slow down. This is because γ-workers have a low UE rate and, once they find a job, they are unlikely to keep it for a long time. Thus, the increase in unemployment among γ-workers takes years to be reabsorbed as many of them go through multiple cycles of unemployment and short-term employment.

It is worth noting that γ-workers are the largest contributor to the initial increase in aggregate unemployment, even though they are the smallest group in the overall population. In contrast, α-workers are the smallest contributor to the initial increase in aggregate unemployment, even though they are the largest group in the overall population. Intuitively, γ-workers have the smallest gains from trade in the labor market and, hence, their employment is most susceptible to a negative productivity shock and to an increase in the generosity of unemployment benefits. In contrast, α-workers have the largest gains from trade in the labor market and, hence, their employment is least susceptible to the lockdown. Moreover, as one can see from Figure 1 and Table 2, γ-workers are overrepresented in some of the industries that are hit hardest by the lockdown. Indeed, the average productivity shock for a γ-worker is 10% larger than for α-workers.

It is also worth pointing out that the share of temporary layoffs is highest for γ-workers (approximately 75%) and lowest for α-workers (approximately 35%). There is a clear intuition behind this result. It takes a long time for an unemployed γ-worker to find a "stable" match, i.e. a match with an idiosyncratic component of productivity that is high enough to make the worker stop searching for something better. Thus, a firm and a γ-worker in a "stable" match prefer to remain in contact (at the costs c and C) rather than to permanently separate. In contrast, it takes a relative short time for an unemployed α-worker to find a new "stable" match. Thus, a firm and an α-worker prefer to permanently terminate their relationship rather than to remain in contact.

The role played by the ex-ante heterogeneity of workers in shaping the recovery can be seen in the dynamics of the unemployment rate in different industries. Panel (a) in Figure 3 shows the excess unemployment rate in construction—an industry with a large fraction of gamma-workers. Panel (b) shows the excess unemployment rate in manufacturing—an industry with a large fraction of α-workers. Even though the initial increase in unemployment is higher in manufacturing, the recovery is much faster because α-workers are more likely to find stable employment after the lockdown is lifted. In the Appendix, we present the behavior of the unemployment rate in every industry.

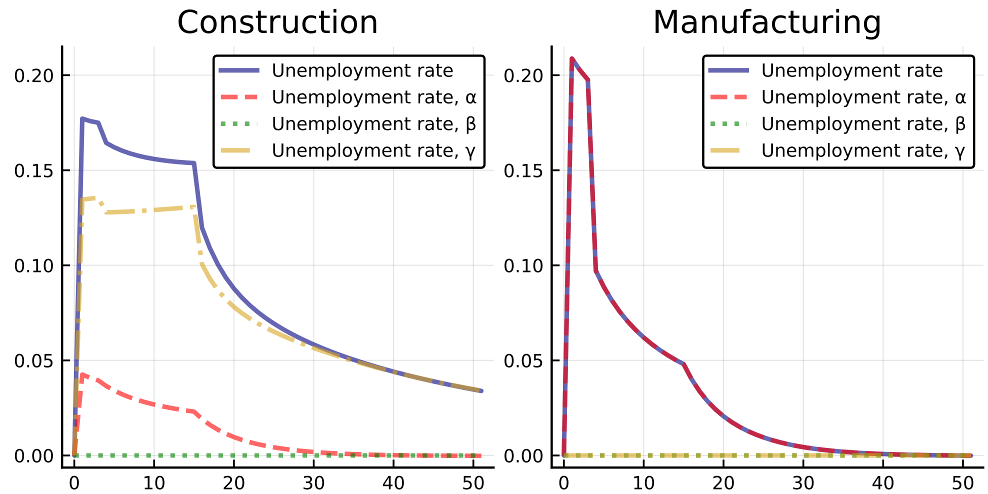

Figure 3: Unemployment dynamics in selected industries

Industry	Δu_j (%)	A_j
Agriculture, Forestry, Fishing and Hunting	3.85	1.2
Mining, Quarrying, and Oil and Gas Extraction	12.29	0.67
Utilities	1.06	1.11
Construction	18.06	0.75
Manufacturing	21.0	0.37
Wholesale Trade	11.82	0.53
Retail Trade	26.25	0.59
Transportation and Warehousing	12.37	0.49
Information	9.8	0.96
Finance and Insurance	1.33	1.16
Real Estate and Rental and Leasing	18.51	0.61
Professional, Scientific, and Technical Services	9.17	0.75
Management of Companies and Enterprises	5.58	1.04
Administrative/Support/Waste Management/Remediation	18.57	1.06
Educational Services	8.12	0.68
Health Care and Social Assistance	21.0	0.49
Arts, Entertainment, and Recreation	55.7	0.13
Accommodation and Food Services	49.06	0.34
Other Services (except Public Administration)	47.62	0.21
Public Administration	0.0	1.24

Table 2: Industry-level unemployment increases and calibrated productivity shocks

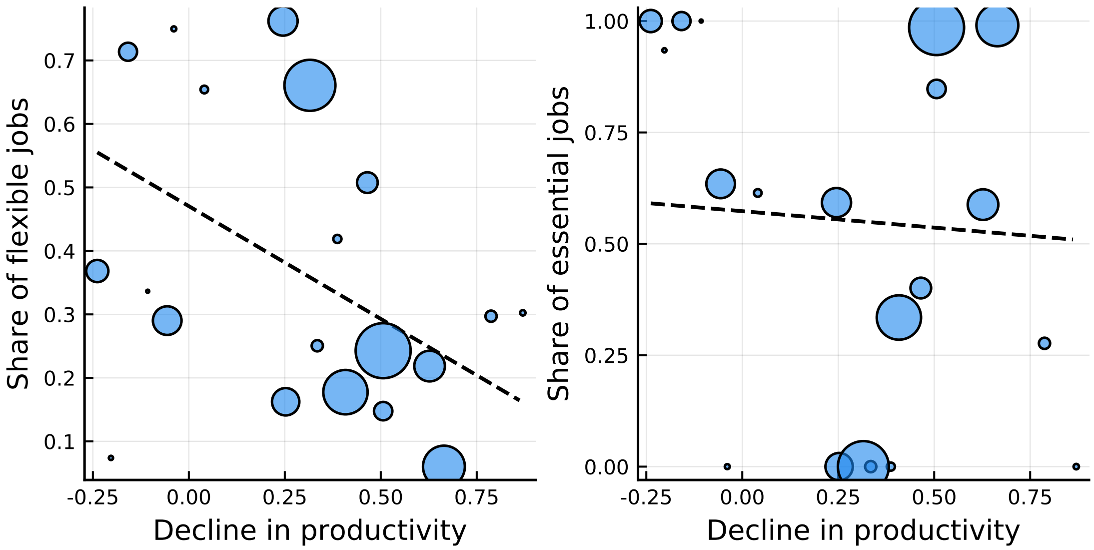

Figure 4: Calibrated productivity shocks vs. flexible and essential jobs

Table 2 shows the industry-specific productivity shocks that we infer from our calibration. The calibrated shocks depend on the composition of workers in the industry—which we estimate from the SIPP—and on the magnitude of the increase in unemployment benefit claims—which we observe for March and April 2020 for several states. As a sanity check, we compare our calibrated productivity shocks with two measures of the exposure of an industry to the lockdown. The first measure is the fraction of workers in industry j that can work remotely. This measure is constructed from the occupational index of "teleworkability" constructed by Dingel and Neiman (2020) using the ONET and then projected on industry j based on its occupational composition. The second measure is a definition of "essential work" for the state of Pennsylvania, where essential workers are those exempted from the lockdown.

Figure 4 contains a scatter plot of the calibrated productivity shock and the fraction of "teleworkable" labor (panel a) and the scatter plot of the calibrated productivity shock and the fraction of "essential" labor (panel b) across 2-digit industries. As one would have expected, both relationships are negative. The strength of the relationship between the calibrated productivity shock and the fraction of "teleworkable" labor is much stronger. Moreover, the employment-weighted average productivity shock in the model is about 35%. The employment-weighted average of the fraction of labor that cannot be done remotely is 45%. The employment-weighted average of the fraction of labor that is both non-essential and cannot be done remotely is 27%. We find it reassuring that our model generates an average shock that is in the same order of magnitude as the fraction of labor that is susceptible to the lockdown.

As mentioned earlier, the recall costs c_i and C_i determine the fraction of workers in permanent and temporary layoffs. Thus, for a given increase in the unemployment rate, the recall costs affect the speed of the recovery. Specifically, the higher are the recall costs, the lower is the fraction of temporary layoffs and the slower is the recovery. It is then important to build some confidence in our choice of c_i and C_i. In our baseline calibration, we set $c_i = 0.05 \cdot y_i$ and $C_i = 0.25 \cdot y_i$ and found that 65% of the increase in unemployment during the lockdown was due to temporary layoffs and 35% to permanent layoffs. This finding is in line with the survey evidence on layoffs during the early stages of the pandemic. Adams-Prassl et al. (2020) survey a representative sample of individuals in the US, conducting multiple waves of

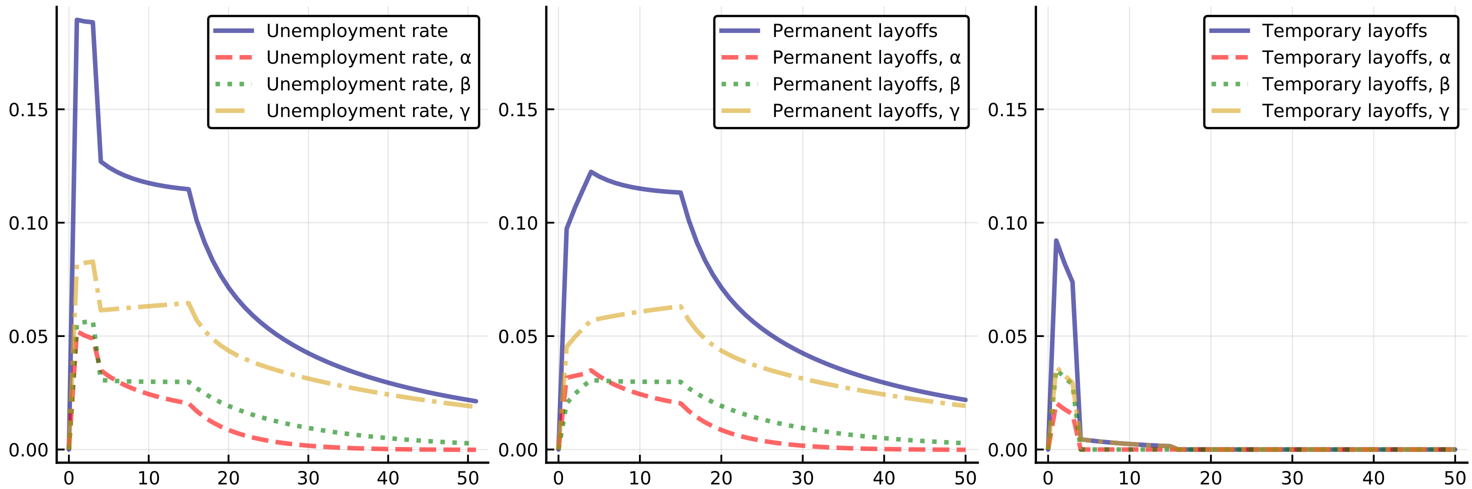

Figure 5: Simulation of pandemic with $c_i = 0.15 \cdot y_i$ and $C_i = 0$

interviews during the first weeks of the pandemic. Individuals could report whether they had lost their job in a permanent way or been furloughed, implying the expectation of being called back. As of the Apr 23 data, the ratio of temporary to permanent lay-offs was 3 : 2. Bick and Blandin (2020) conduct a similar survey, again asking whether individuals who separated from their employer expected the layoff to be temporary, using language similar to question in the CPS. They found approximately 50% of separations were expected to be temporary. Overall, our calibration of c_i and C_i is conservative, in the sense that our model generates more temporary lay-offs than what found in these surveys.

The ratio between the cost of exercising the recall option, C_i, and the cost of maintaining the recall option, c_i, affects the time at which temporarily deactivated relationships are recalled. Figure 5 shows the simulation of the recession for $c_i = 0.15 \cdot y_i$ and $C_i = 0$, rather than for $c_i = 0.05 \cdot y_i$ and $C_i = 0.25 \cdot y_i$. By lowering the cost of exercising the recall option while increasing the cost of maintaining the recall option, the fraction of layoffs that are temporary and permanent does not change by much (it goes from 65 : 35% to about 50 : 50%). For this reason, the medium-term effects of the lockdown do not change by much either (the excess unemployment rate 50 months out is still about 2.5%). However, the timing of recalls does change. In particular, most of temporarily laid-off workers are recalled as soon as the lockdown is lifted.

From the perspective of policy, it is interesting to see the labor market consequences of extending the lockdown. Figure 6 below illustrates the results of the simulated recession when the economy is kept under lockdown for 6 months rather than 3, and the period of uncertainty lasts 9 rather than 12 months. Because of the extended lockdown, the unemployment rate remains close to its peak for a longer period of time. Yet, once the economy enters the recovery state, the unemployment rate is essentially the same as in the baseline calibration. In this sense, extending the lockdown does not seem to have nefarious effects on unemployment in the medium-run. We urge our readers, however, to take this finding with a grain of salt, as it may depend on our conservative assumptions about the effect of the lockdown on the survival rate of temporarily deactivated relationships.

Lastly, we want to point out that the model can also generate a "V-shaped" recession, i.e. a recession in which the initial increase in unemployment is quickly reabsorbed after the end of the lockdown. The

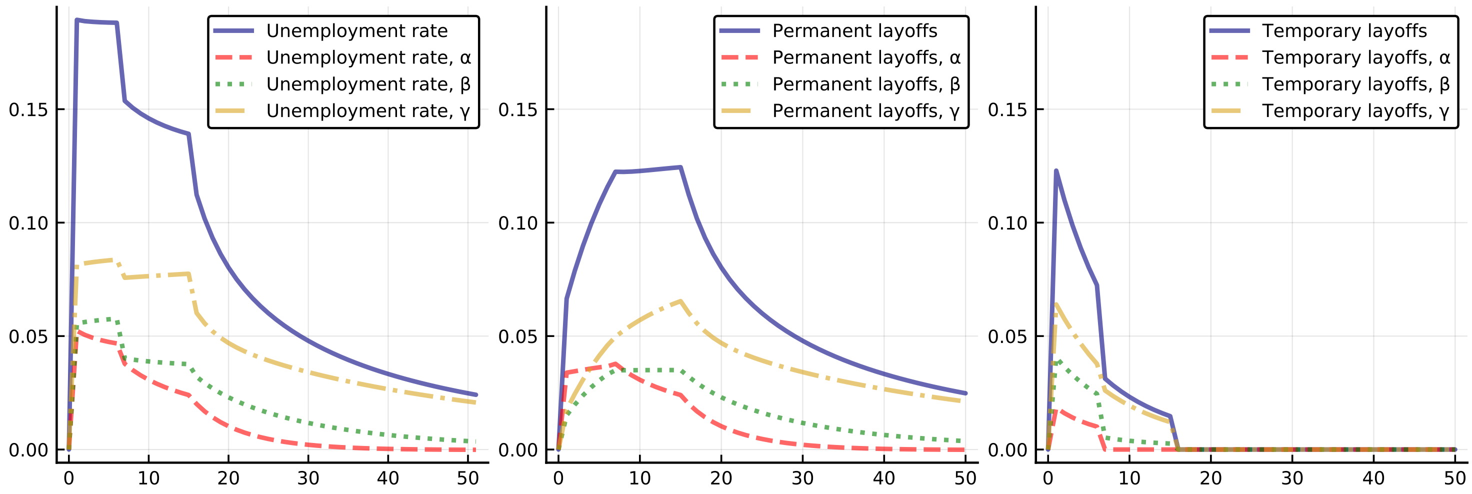

Figure 6: Simulation of pandemic with 6 months of lockdown, 9 months of uncertainty

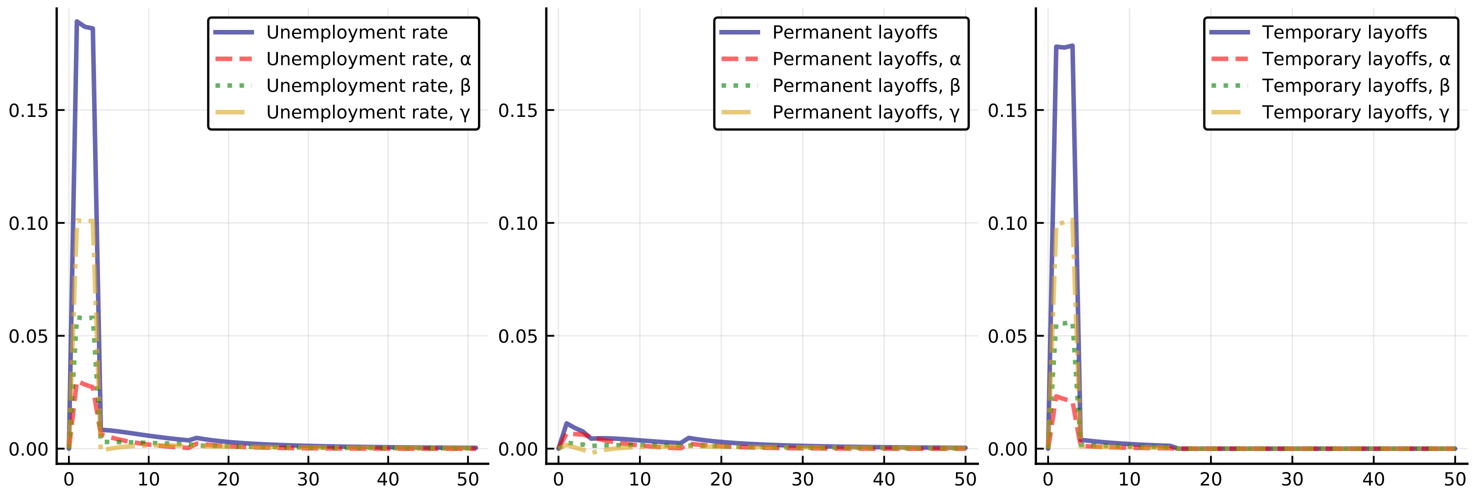

Figure 7: V-shaped simulation of pandemic

model generates a V-shaped recession when the initial increase in unemployment is almost entirely driven by temporary layoffs and, as soon as the lockdown is over, firms find it optimal to recall all of the temporarily laid-off workers.[4] Hence, the model generates a V-shaped recession when c_i and C_i are small and B_U is close to 1.

Figure 7 illustrates the simulation of the pandemic recession with $c_i = C_i = 0$ and $B_U = 1$. As the economy enters the lockdown, the unemployment rate increases by 19 percentage points. About 18 percentage points of this increase are due to temporary separations between workers and firms, while the remaining 1 percentage point is due to permanent separations. As the economy exits the lockdown, nearly all of the workers on temporary layoff are recalled by their employers, and the unemployment rate returns within 1 percentage point of its steady-state level.

While the model can generate a V-shaped recession, it does so by producing some implausible outcomes.

[4]In principle, the model could also generate a V-shaped recession if the vast majority of workers entering unemployment during the lockdown were of type α. However, our calibration of the type distribution across industries and of the shock distribution across industries rules out this possibility.

First, 95% the initial increase in the unemployment rate is due to temporary layoffs and only 5% is due to permanent layoffs. In the recent surveys of Adams-Prassl et al. (2020) and Bick and Blandin (2020), at least 40% of workers who became unemployed at the beginning of the recession state to have no expectation of being recalled by their previous employer. Second, when the costs associated with temporary layoffs are low, it takes a smaller productivity shock to generate the same increase in unemployment during the lockdown. Indeed, the employment-weighted productivity shock required to generate a 19 percentage point increase in unemployment is only 1.4%. This is an order of magnitude lower than the employment-weighted average of work that cannot be done remotely (45%), and much lower than the employment-weighted average of the fraction of work that is both non-essential and cannot be done remotely (27%).

Let us conclude by pointing out that underneath the results presented in this section—results that are aggregated either at the economy level or at the industry level—there is a wealth of additional results about individual workers, including the size of their earnings losses during the lockdown and the speed at which these losses are recouped.[5] We decided not to report these disaggregated results not because we deem them uninteresting, but for the sake of conciseness.

[5]Let us just say that our model does an excellent job at reproducing the size of earnings losses documented in Jacobson, LaLonde and Sullivan (1993) and Davis and von Wachter (2011).

A Unemployment rate IRFs by industry

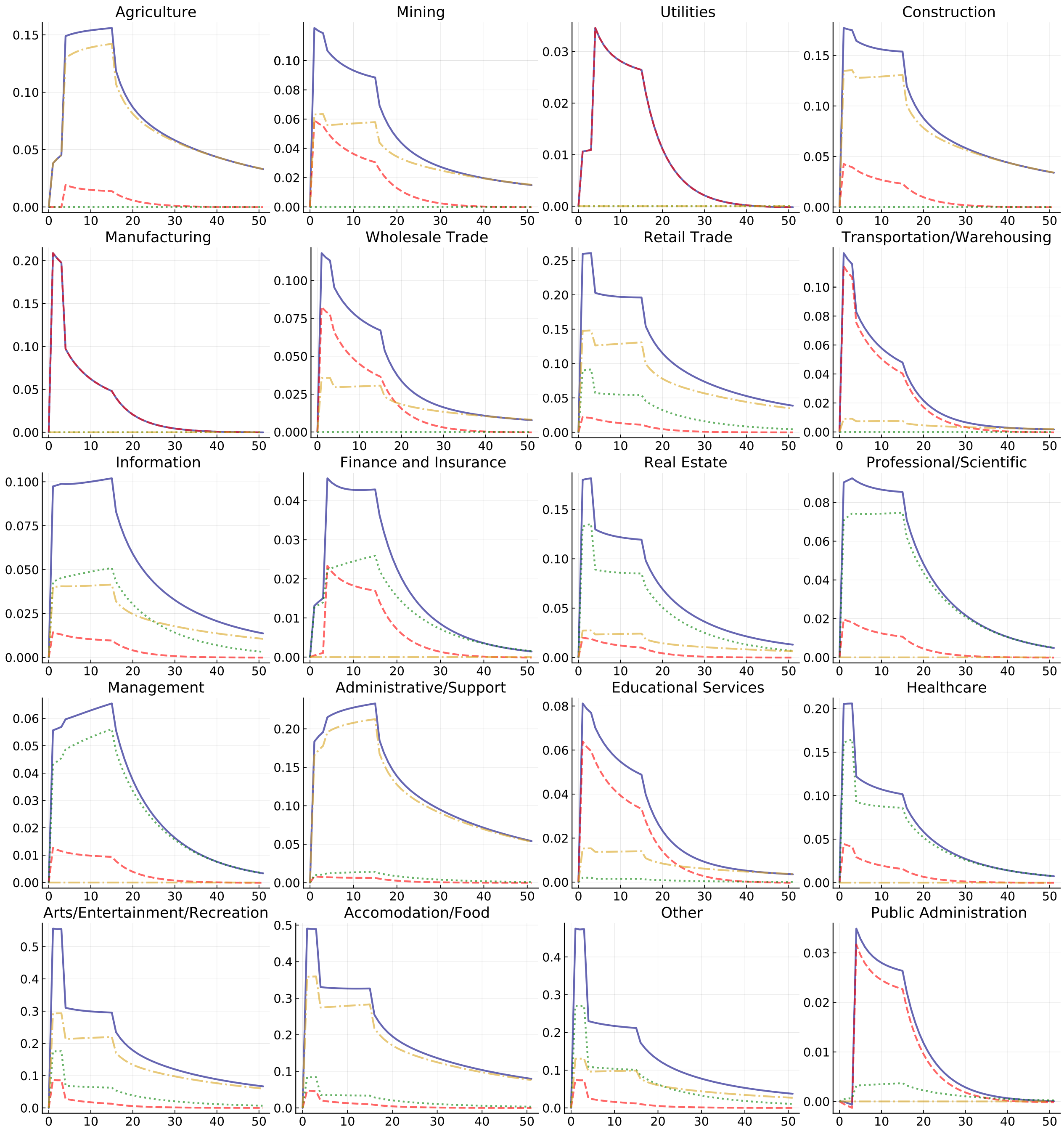

Figure 8: Pandemic simulation by industry

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