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ABSTRACT

The Lockdown Impact on Unemployment for Heterogeneous Workers*

We develop a multi-sectoral matching model to predict the impact of the lockdown on the US unemployment, considering the heterogeneity of workers to account for the contrasted impacts across various types of jobs. We show that separations and business closures that hit the workers with the first level of education explains the abruptness of the unemployment rise. The existence of significant congestion externalities in the hiring process suggests that a comeback to the pre-crisis unemployment level could be reached in 2024 in a scenario with a double wave. In the same scenario, a calibration on French data leads to more pessimistic forecasts with a comeback to the pre-crisis unemployment level expected until 2027.

JEL Classification: E24, E32, J64

Keywords: COVID-19, unemployment dynamics, search and matching, worker heterogeneity

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1 Introduction

COVID-19 crisis has led to an unprecedented increase in unemployment after the lockdown bombshell due to health and sanitary concerns. This stay-at-home instruction has affected the economy on different aspects and made it extremely difficult to predict how the labor market will adjust on one hand and to assess the duration needed to converge towards the natural unemployment path on the other one. Moreover, behind the big picture of aggregated dynamics, there are also some important heterogeneities among workers: the repercussion of the “lockdown” is not the same for everyone, leading to a contrasted unemployment dynamics. Furthermore, even if the lockdown aimed directly at a subset of population, there was a substitution effect due to consumer preferences, which affected the overall economy and made the effect, which was initially type-specific, spread to different economic sectors. Finally, this shock also led to some extreme decisions as business closures and activity suspensions.

In this paper, we aim to deal with the following questions: how to explain the rapid and large rise in unemployment? Which type of workers is more affected by this sudden lockdown? What are the type-specific unemployment dynamics? How does these inequalities translate on the aggregated level? What are the prediction of the model for the unemployment persistence?

To answer these questions, we use an original extension of the Diamond-Mortensen-Pissarides (DMP) model. Indeed, all these questions challenge the DMP model that thus need to be extended. Unemployment rate can double during a crisis: this underlines that the elasticity of unemployment to the business cycle must be very large. This doubling of unemployment rate can occur within a month, but we have never experienced a rapid decline in unemployment.¹ These asymmetries and this persistence of unemployment dynamics are difficult to explain by the basic version of the DMP model. Hence, to this extent, we show that worker heterogeneity, endogenous separations, time-varying microeconomic risks over the business cycle and externalities in the hiring costs are crucial to explain the US labor market fluctuations with a Search and Matching (SaM) model.

Since Robin (2011) paper, it is well established that worker heterogeneity matters for explaining the aggregate unemployment dynamics.² Worker heterogeneity matters be-

¹Hall and Kudlyak (2020) show that, during periods of recovery over the past 70 years, we observe a reduction of 0.5 points in unemployment per year, which suggests that the current crisis will be resolved in 15 years.

²Lise and Robin (2017), Ferraro (2018) & Ferraro (2020) and Adjemian et al. (2019) are other examples of SaM models where worker heterogeneity improves the ability of the DMP model to reproduce labor

cause a small fraction of the population can be highly sensitive to the business cycle and thus generates large unemployment in recessions through larger separations. In order to amplify the response of separations and makes it more persistent, we introduce a counter-cyclical microeconomic risk. In fact, uncertainty increases during periods of exceptional recession.³ In particular, Bloom (2009) and Bloom et al. (2018) document the non-stability over time of the dispersion of productivities at the firm level (microeconomic risks) and the counter-cyclicity of this dispersion with the business cycle.⁴ Regarding the type of heterogeneity used in this study, we retain a heterogeneity fixed over time in order to be consistent with a model without mobility between groups of agents: this is why we choose groups defined by the level of education (*i.e* by diploma) , which is generally fixed during working life.⁵ The heterogeneity by level of education seems to be well suited to predict the workers' type specific effects of the lockdown measures. Indeed, even a homogeneous lockdown can have heterogeneous effects. Prassl et al. (2020) show that the workers ability of being able to do a high share of their tasks from home is limited for some occupations, mostly for low income professions (telework share of 37% for those earning less than 35,000\$, to be compared with 65% for those earning more than 70,000\$ by year). This flexibility of work organization leads to significant gaps in job stability: among workers who report having had a job four weeks ago, those with low levels of annual income report a higher probability of job loss due to COVID-19 (15% for those earning less than 19,000\$ by year and only 5% for those earning more than 70,000\$ by year). Another way to identify the unequal impacts on heterogeneous workers of the lockdown measures induced by the COVID-19, is proposed by Fana et al. (2020). Using the EU labor force survey, they first construct five categories of sectors according to the likely impact of the confinement measures: (*i*) essential and fully active; (*ii*) active but via telework; (*iii*) mostly essential and partly active, but not teleworkable; (*iv*) mostly non-essential and inactive, not teleworkable; and (*v*) closed. Secondly, they show that the most negative effects of the lockdown measures are concentrated on the low skilled workers.⁶ In France, for example, the average wage percentile of jobs that can be done

market fluctuations.

³See Baker et al. (2020) for an analysis of changes in uncertainty since the start of the COVID-19 crisis.

⁴Kandoussi and Langot (2020) show that a time-varying risk improves the ability of the DMP model to explain US unemployment dynamics.

⁵This distinguish our modeling strategy from the one followed by Gregory et al. (2020) who define they three workers groups on the basis of their “performance” with respect to the labor market transitions.

⁶Indeed, the sectors forcefully closed by decrees (sector (*v*) of their decomposition, that includes hospitality, personal services, leisure activities, etc.) are characterised by low wages and high separation rates.

by teleworking is 64, whereas it is only 35 for jobs that can be closed.

After a recession, the time of recovery is characterized by a slow decline in unemployment, whatever the worker's diploma.⁷ The sluggishness of the hiring process contrasts with the abruptness of the separations leading to strong asymmetries in unemployment dynamics.⁸ Nevertheless, the speed of convergence of the DMP model is too fast compared to what we observe, leading to largely underestimating the impact of recessions.⁹ Consequently, we introduce a congestion externality as in Hall and Kudlyak (2020), that rises the unit cost of vacancy posting in recession, for all jobs.

Therefore, to forecast the possible impact of the COVID-19 crisis, we start by calibrating the model in order to reproduce the impact of the 2008 financial crisis using US labor market data. Even if these two crises are not similar in nature, having a model which is able to reproduce the observed asymmetric adjustments of the US labor market (rapid increase and slow recovery) on one hand, and the induced inequalities on the other (the least qualified are strongly impacted) is essential for forecasting the impact of the current crisis.

Using this calibrated model, we first identify the size of the shocks necessary to reproduce the first 3 observed months of the current crisis. Indeed, a problem with the COVID-19 crisis comes from the magnitude of the shock hitting each sector. Even for a given lockdown duration, the direct impact of the lockdown measures are different across sectors: the restrictions on the production process, the induced demand contraction as well as the different subsidies directed to each profession and/or worker are sector specific. This suggests that the size shock must be specific to each sector. Using our calibrated model and the observations of the US aggregates since February 2020, we first reveal the size of the sector specific shocks that allows the model to replicate the US data known since the beginning of the crisis: for those without a high school diploma, the lockdown reduces by 90% the revenues they generate for firms, while those who own a bachelor degree or more sees it decrease only by 20%. Secondly, our model predicts that separations induce the spike in unemployment, which are strongly concentrated on workers with at most a high school diploma and with activity closings for those with a less than high school diploma.

⁷As Cairo and Cajner (2016) show, the job finding rates by diploma are very close to each other, both in levels and in variations. Heterogeneity therefore seems to be less important in explaining the recoveries, except obviously that the initial unemployment excess after a crisis is largely higher for the low skilled workers.

⁸For the asymmetries on the US labor market and the ability of the DMP model to reproduce them, see Ferraro (2018) & Ferraro (2020) and Adjemian et al. (2019).

⁹See Gorry et al. (2020) and Pries (2004) for a discussion of this point.

Indeed, our general equilibrium analysis allows us to detect the markets for which an equilibrium price does not exist, and thus on which there are no transactions, i.e. where business activities are closed. For the recovery, it predicts a fairly large persistence of unemployment, even if the lockdown period is limited, and a return to the pre-crisis situation that can be expected in 2024 in the case of a second wave of the epidemic that might lead to another lockdown in October 2020.¹⁰ Finally, a comparison with a calibration based on French data, shows that low job finding rates lead to more persistent and hence very large effects of the crisis. In the case of the double epidemic wave, the return to the pre-crisis situation could only be expected by 2027, and this even if the lockdown is accompanied by a more generous government assistance measures.

The remaining of this paper is as follow: Section 2 presents the model which results will be presented in Section 3. Section 3 first discusses the calibration in 3.1 and thus the fit of the 2008 crisis, and present in section 3.2 the projections for the COVID-19 impact on US and in section 3.3 the ones for France. Finally, Section 4 concludes.

2 Model

We aim at analysing the effect of aggregate shocks with a SaM model using a general equilibrium approach. With respect to the canonical Mortensen and Pissarides (1994) model, we add two important externalities. Both aim to account for the greatest difficulties in times of crisis to have good information on the workforce. Thus, it is assumed that units recruitment costs will increase when unemployment diverges from its long-term value, which introduces congestion externality on hirings. It is also assumed that the dispersion of idiosyncratic productivities is greater when unemployment diverges from its long-term value, which makes microeconomic uncertainty counter-cyclical. We place ourselves in the context of segmented labor markets where a qualification can therefore achieve only one task. The interactions between these markets result from the household's consumption choices which make it possible to determine the relative prices in each period. Finally, in order to meet the financing needs of companies wishing to reopen after activity cessations, we introduce savers. Hence, the population is divided in two subgroups, with only a mass $1 - \varphi$ having access to financial markets. The workers are heterogeneous with respect to their educational attainment s . The share of each skill within the mass of worker is ω_s .

¹⁰As Kissler et al. (2020)'s epidemiological analysis suggests, a second wave is highly likely. Therefore, we present the implications of two scenarios, the first with one wave (March) and the second with two waves (March and October).

2.1 Financially constrained agents: the workers

workers are risk neutral and are characterized by their skill $j \in \mathcal{J}$. Preferences of each worker i are defined over a set of goods $s \in \mathcal{S}_t$. When all markets are open, \mathcal{S}_t is such that $s = 1, \dots, S$ where S is the maximal number of varieties. Otherwise, $\dim(\mathcal{S}_t) < S$ with a cardinal denoted $S_{n,t}$. The preferences of each agent i with the skill j are defined as follows:

$$C_{i,j,t}^L = S_{n,t}^{\frac{1}{1-\sigma}} \left(\sum_{s \in \mathcal{S}_t} (C_{i,j,s,t}^L)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

Her resource constraint is given by

$$I_{i,j,t} = \sum_{s \in \mathcal{S}_t} p_{s,t} C_{i,j,s,t}^L = p_t C_{i,j,t}^L \quad \text{for} \quad I_{i,j,t} = \{w_{i,j,t}(\alpha), b_{i,j}\} \quad \forall j \in \mathcal{J}$$

where the consumer price index is defined by

$$p_t = \left(\frac{1}{S_{n,t}} \sum_{s \in \mathcal{S}_t} p_{s,t}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

and $w_{i,t}(\alpha)$ denotes the real wage (the nominal wage deflated by the Consumer-Price-Index, p_t) of the employed worker and b_i is the real unemployment benefit of the unemployed worker.

The optimal demands for each good $s \in \mathcal{S}_t$ is:

$$C_{i,j,s,t}^L = \left(\frac{p_{s,t}}{p_t} \right)^{-\sigma} \frac{C_{i,j,t}^L}{S_{n,t}}$$

The value functions of each worker are

$$\begin{aligned} W_{i,j,t}(\alpha) &= w_{i,j,t}(\alpha) + \beta_t \left[(1 - s_{j,t+1}) \int_{\alpha_{j,t+1}^r}^{\infty} W_{i,j,t} \frac{dG(\alpha)}{1 - G(\alpha_{j,t+1}^r)} + s_{j,t+1} U_{i,j,t+1} \right] \\ U_{i,j,t} &= b_{i,j} + \beta_t \left[f_{j,t+1} (1 - s_{j,t+1}) \int_{\alpha_{j,t+1}^r}^{\infty} W_{i,j,t} \frac{dG(\alpha)}{1 - G(\alpha_{j,t+1}^r)} + (1 - f_{j,t+1} (1 - s_{j,t+1})) U_{i,j,t+1} \right] \end{aligned}$$

where β_t is the time-varying discount factor, $s_{j,t}$ the endogenous job separation rate, and $f_{j,t}$ the meeting rate between an unemployed job seeker and a vacant job position.

2.2 Financially unconstrained agents: the capitalist

The capitalist aims to maximize the sum of his discounted utility given by :

$$\sum_{t=0}^{\infty} \beta_t^t \left(\frac{(C_t^K)^{1-\nu}}{1-\nu} + A_b B_t \right)$$

where C_t^K denotes the baskets of consumption goods and B_t the composite storable goods that provides utility. The baskets of consumption (C_t^K) and investment (I_t^K) goods have the same CES function than for the worker:

$$C_t^K = S_{n,t}^{\frac{1}{1-\sigma}} \left(\sum_{s \in \mathcal{S}_t} (C_{s,t}^K)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \quad \text{and} \quad I_t^K = S_{n,t}^{\frac{1}{1-\sigma}} \left(\sum_{s \in \mathcal{S}_t} (I_{s,t}^K)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

Storable goods accumulates as follows:

$$B_{t+1} = (1 - \delta)B_t + S_{n,t}^{\frac{1}{1-\sigma}} \left(\sum_{s \in \mathcal{S}_t} (I_{s,t}^K)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} - \frac{\varphi}{1 - \varphi} \sum_{s \notin \mathcal{S}_t} \omega_s \psi_s \kappa_{s,t} V_{s,t}$$

where we assume that the capitalists finance the firm's reopening costs (the last term of the last equation). Because markets $s \notin \mathcal{S}_t$ are not open at this period t , the unit cost of each transaction between the capitalist and the reopening firms is ψ_s .

The budgetary constraint of this representative agent is:

$$\begin{aligned} C_t^K + I_t^K &= \frac{\varphi}{1 - \varphi} \left(\sum_{s \in \mathcal{S}_t} \omega_s D_{s,t} - \sum_{s \notin \mathcal{S}_t} \omega_s \psi_s \kappa_{s,t} V_{s,t} \right) \equiv \mathcal{R}_t \\ B_{t+1} &= (1 - \delta)B_t + \mathcal{R}_t - C_t^K \end{aligned}$$

where $D_{s,t}$ are the dividends earned from the firms of sectors $s = 1, \dots, S$. When $s \in \mathcal{S}_t$, this dividend is positive whereas when $s \notin \mathcal{S}_t$ this dividend is negative and equals to $\kappa_{s,t} V_{s,t}$ for each firm planing to reopen in the next period.

The Euler equation is:

$$(C_t^K)^{-\nu} = \beta [A_b + (1 - \delta)(C_{t+1}^K)^{-\nu}]$$

and the intertemporal choices are given by:

$$C_{s,t}^K = \left(\frac{p_{s,t}}{p_t} \right)^{-\sigma} \frac{C_t^K}{S_{n,t}} \quad \text{and} \quad I_{s,t}^K = \left(\frac{p_{s,t}}{p_t} \right)^{-\sigma} \frac{I_t^K}{S_{n,t}} \quad \text{for } s \in \mathcal{S}_t$$

In the following, we assume that $B_t > 0, \forall t$.¹¹ This assumption is sustainable because the pricing of the vacancy costs prior to reopening (ψ_s) can be arbitrary low. The particular assumptions made on the capitalist preferences lead the consumption to be autonomous. This property implies that all the income fluctuations of the capitalists are absorbed by changes in their inventories B_{t+1} .¹²

¹¹Indeed, we must have $B_t \geq 0, \forall t$. When this constraint is binding, this implies that capitalists can not finance the reopening costs of the firms, leading them to close, whatever the expected profits.

¹²With the solution for the consumption $C_t^K = \left(\frac{\beta A_b}{1 - \beta(1 - \delta)} \right)^{\frac{1}{\nu}}$, we have $B_{t+1} - (1 - \delta)B_t = \mathcal{R}_t - C_t^K$.

2.3 Labor market flows

As in the DMP model, a matching function generates meetings, whereas separations result from the selection of workers that are more productive than an endogenous threshold. The labor markets of each skill $j \in \mathcal{J}$ are segmented. We assume that each skill j can produce only one type of product s . At the beginning of each period t , the number of workers inside the firm is the sum of the hirings in the previous period ($q_{s,t-1}V_{s,t-1}$) and the previous employment stock ($N_{s,t-1}$). Then, in each firm i of the sector s , an idiosyncratic shock takes place and the productivity of worker ($\alpha_{i,s,t}$) is discovered. There are separations if $\alpha < \alpha_{i,s,t}^r$. This threshold gives the mass of endogenous separations. Note that the pool of separation includes old and new matches. The microeconomic shock α is drawn in the time varying distribution $G_{s,t}(\alpha)$, which is a log-normal distribution with mean μ_G and a variation $\sigma_{s,t}$. In order to account for the increase of microeconomic risks in recession, we assume that

$$\sigma_t = \sigma_G \left(\frac{U_t}{U} \right)^\xi$$

where the current level of unemployment rate U_t and its long run value U are taken as given at the level of the firm i on the labor market segment s . The parameter ξ controls the impact of the recession on σ_t .¹³ Once the information on productivity is revealed, the stock of employment available for production is determined. Hence, the wage bargaining can occur and finally, production takes place. It is only at the end of period t that stocks of unemployment ($U_{s,t}$) and employment ($N_{s,t}$) are given allowing to determine new matches that occur through the choice of $V_{s,t}$, based on $q_{s,t}$.

Workers and firms direct their search efforts on the one submarket corresponding then to a sector s or a skill j , with $j = s$. Following Den Haan et al. (2000), the matching function for each sector is

$$M_s(U_{s,t}, V_{s,t}) = \frac{U_{s,t}V_{s,t}}{(U_{s,t}^\tau + V_{s,t}^\tau)^{1/\tau_s}}$$

ensuring that the probabilities for an unemployed worker to find a job per unit of time

$$f_s(\theta_{s,t}) = \frac{M(U_t, V_{s,t})}{U_{s,t}} = (1 + \theta_{s,t}^{-\tau_s})^{-1/\tau_s}$$

and the vacancy to be filled

$$q_s(\theta_{s,t}) = \frac{M(U_{s,t}, V_{s,t})}{V_{s,t}} = (1 + \theta_{s,t}^{\tau_s})^{-1/\tau_s}$$

¹³The counter-cyclicality of the firm's level microeconomic risks is documented by Bloom (2009) and Bloom et al. (2018)

are in the interval $[0; 1]$. The law of motion of employment is:

$$N_{s,t} = (1 - s_s)(1 - G_{s,t}(\alpha_{s,t}^r))(N_{s,t-1} + q(\theta_{s,t-1})V_{s,t-1})$$

where, $0 < s_s < 1$ is the exogenous probability of job destruction. The job separation rate is defined by $JSR_t \equiv s_{s,t} = s_s + (1 - s_s)G_{s,t}(\alpha_{s,t}^r)$, and gives the INs to unemployment, given the information of the period t . The job finding rate is defined by $JFR_t \equiv f_{s,t} = (1 - s_{s,t+1})f_s(\theta_{s,t})$, and gives the OUTs to unemployment taking into account the information of period t , but also the information of period $t + 1$. Finally, the normalization of the population size to unity leads to $\varphi \sum_{s=1}^S \omega_s(U_{s,t} + N_{s,t}) + (1 - \varphi) = 1$.

2.4 Firms

For a firm i of the sector s , the hirings result from a search process that consists to post the number of vacancies $V_{i,s,t}$ that will be matched with unemployed workers with a probability $q_{s,t}$, not controlled by the firm. The unit cost, in production units, of each vacancy is given by

$$\kappa_{i,s,t} = \kappa_{s,t} = \kappa_s \left(\frac{U_{s,t}}{U_s} \right)^{\gamma_s} \quad \forall i$$

where both the current level of unemployment rate $U_{s,t}$ and its long run value U_s are taken as given at the level of the firm i on the labor market segment s , thus leading to interpret the time varying component of the vacancy cost as a congestion externality.¹⁴ Given that γ_s depend on s , this congestion externality is sector-specific. Unit costs are higher in recession, because at this time, each vacant job (which are scarce in those periods) receives a very large number of applications (the number of unemployed being important): recessions increase, therefore, the cost of treatment of each application. Blanchard and Diamond (1994) were the first to give foundations to these counter-cyclical unit costs, based on the existence of exchange externalities: they show that in a labor market where entrepreneurs prefer hiring short-term unemployed workers, recessions lead to an increase in the share of long-term unemployed who, then, congest the hiring process. Hall and Kudlyak (2020) show why this congestion effect is important for the DMP model to reproduce the observed persistence of unemployment after a recession. Moreover, Engbom (2019) and Molavi (2018) suggest that countercyclical hiring unit costs are supported by the data.

¹⁴We choose the same functional form than Hall and Kudlyak (2020), but we introduce a sector specific parameter γ_s that induces a sector specific congestion externality.

The production function is¹⁵

$$Y_{s,t} = A_{s,t}A_tN_{s,t}\frac{1}{1-G_{s,t}(\alpha_t^r)}\int_{\alpha_{s,t}^r}^{+\infty}\alpha dG_{s,t}(\alpha)$$

where $A_{s,t}$ and A_t are respectively the skill specific and the aggregate productivity.

The firm's profits are:

$$D_{s,t} = p_{s,t}Y_{s,t} - N_{s,t}\frac{1}{1-G_{s,t}(\alpha_{s,t}^r)}\int_{\alpha_{s,t}^r}^{+\infty}w_{s,t}(\alpha)dG_{s,t}(\alpha) - \kappa_{s,t}V_{s,t}$$

Denoting $\tilde{\alpha}_{s,t} = \frac{\int_{\alpha_{s,t}^r}^{+\infty}\alpha dG_{s,t}(\alpha)}{1-G_{s,t}(\alpha_{s,t}^r)}$ and $\tilde{w}_{s,t} = \frac{\int_{\alpha_{s,t}^r}^{+\infty}w_{s,t}(\alpha)dG_{s,t}(\alpha)}{1-G_{s,t}(\alpha_{s,t}^r)}$, the first-order conditions of the firm's program lead to the following inter-temporal job destruction and job creation conditions:¹⁶

$$\begin{aligned} J_{s,t}(\alpha_{s,t}) &= p_{s,t}A_{s,t}A_t\alpha_{s,t} - w(\alpha_{s,t}) + \beta_t(1-s_{s,t+1})J_{s,t+1} \quad \forall \alpha_{s,t} \geq \alpha_{s,t}^r \\ J_{s,t}(\alpha_{s,t}^r) &= 0 \\ J_{s,t} &= p_{s,t}A_{s,t}A_t\tilde{\alpha}_{s,t} - \tilde{w}_{s,t} + \beta_t(1-s_{s,t+1})J_{s,t+1} \\ \frac{p_{s,t}\kappa_{s,t}}{q(\theta_{s,t})} - \lambda_{s,t} &= \beta_t(1-s_{s,t+1})J_{s,t+1} \end{aligned}$$

where $J_{s,t} = \frac{\partial \mathcal{V}_{s,t}}{\partial N_{s,t}}$ is the marginal value of employment that can also be defined by $J_{s,t} \equiv \frac{\int_{\alpha_{s,t}^r}^{+\infty} J_{s,t}(\alpha)dG_{s,t}(\alpha)}{1-G_{s,t}(\alpha_{s,t}^r)}$ where $J_{s,t}(\alpha)$ is the marginal value of a job after the realization of the idiosyncratic productivity α . Because $J_{s,t}(\alpha) \geq 0, \forall \alpha \geq \alpha_{s,t}^r$, the average job value, defined by $J_{s,t}$ is necessary positive. The intertemporal job destruction condition indicates that the current losses ($p_{s,t}A_{s,t}A_t\alpha_{s,t}^r - w_{s,t}(\alpha_{s,t}^r)$) must be compensated by the expected future gains generated by the job. The intertemporal job creation condition is equalizing the marginal costs of hiring at time t to the firm's marginal value of hiring which is represented by its marginal benefits of hiring at time $t+1$ discounted to t with the stochastic discount factor β_t . The hirings are based on the expectations of this average value of a job $J_{s,t+1}$, as α is revealed after the contact.

The Kuhn-Tucker conditions are given by:

$$q_s(\theta_{s,t})V_{s,t} \geq 0, \quad \lambda_{s,t} \geq 0, \quad \text{and} \quad \lambda_{s,t}q_s(\theta_{s,t})V_{s,t} = 0$$

¹⁵In the following, we omit for simplicity the index i that denotes the firm i in each sector s because the equilibrium is symmetrical within sectors.

¹⁶See Appendix A for more details on the firm's problem solutions.

Regime 1. If the expectation of the average job value, discounted and reduced by the expected separation rate $\beta_t(1 - s_{s,t+1})J_{s,t+1}$ is sufficiently large to lead $V_{s,t} > 0$, then $\lambda_{s,t} = 0$. In this case the dynamics are given by

$$0 = p_{s,t}A_{s,t}A_t\alpha_{s,t}^r - w_{s,t}(\alpha_{s,t}^r) + \frac{p_{s,t}\kappa_{s,t}}{q(\theta_{s,t})}$$

$$\frac{p_{s,t}\kappa_{s,t}}{q_s(\theta_{s,t})} = \beta_t \left[(1 - s_{s,t+1}) \left(p_{s,t+1}A_{s,t+1}A_{t+1}\tilde{\alpha}_{s,t+1} - \tilde{w}_{s,t+1} + \frac{p_{s,t+1}\kappa_{s,t+1}}{q_s(\theta_{s,t+1})} - \lambda_{s,t+1} \right) \right]$$

Note that when the firm cannot sell today ($p_{s,t}$ does not exist) but expects a recovery, it can borrow resources from the capitalist and then restarts its activity even after activity suspension in period t .

Regime 2. If $\beta_t(1 - s_{s,t+1})J_{s,t+1}$ is sufficiently low to lead $V_{s,t} = 0$, then $\lambda_{s,t} > 0$. When $V_{s,t} = 0$, we have $\theta_{s,t} = 0 \Leftrightarrow q(\theta_{s,t}) \rightarrow 1$. Therefore the dynamics are given by

$$0 = p_{s,t}A_{s,t}A_t\alpha_{s,t}^r - w_{s,t}(\alpha_{s,t}^r) + (p_{s,t}\kappa_{s,t} - \lambda_{s,t})$$

$$\lambda_{s,t} = p_{s,t}\kappa_{s,t} - \beta_t \left[(1 - s_{s,t+1}) \left(p_{s,t+1}A_{s,t+1}A_{t+1}\tilde{\alpha}_{s,t+1} - \tilde{w}_{s,t+1} + \frac{p_{s,t+1}\kappa_{s,t+1}}{q_s(\theta_{s,t+1})} - \lambda_{s,t+1} \right) \right]$$

When the solution is constrained at $\theta_{s,t} = 0$, then we have $N_{s,t} = (1 - s_s)(1 - G_{s,t}(\alpha_{s,t}^r))N_{s,t-1}$ until $\theta_{s,t+n} > 0$ in n periods. Note that, it is possible to reach $N_{s,t} = 0$ if $\alpha_{s,t}^r$ leads to $G_{s,t}(\alpha_{s,t}^r) = 1$.

2.5 Wage

To determine the equilibrium wage, we use a simple sharing rule of a generalized Nash bargaining process between the worker and the firm, which is given by:

$$w_{s,t}(\alpha) = \eta_s(p_{s,t}\alpha A_s A_t + p_{s,t}\kappa_{s,t}\theta_{s,t}) + (1 - \eta_s)b_s$$

where $\eta_s \in (0, 1)$ is the heterogeneous workers' relative bargaining weight and b_s is the heterogeneous workers' flow value of unemployment activities. For a given bargaining weight, the higher the costs of filling a vacancy and the more productive the worker, the higher the wages earned.

2.6 General Equilibrium

In the following, we normalize the consumer-price index $p_t = 1, \forall t$.

Demand side. Given that the baskets of consumption and inventories are described by the same CES functions, the aggregate demand for each sectors ($Y_{s,t}^D$) is given by

$$Y_{s,t}^D = p_{s,t}^{-\sigma} \left(\frac{\varphi \sum_{j \in \mathcal{S}_t} \omega_j C_{j,t}^L + (1 - \varphi) (C_t^K + I_t^K)}{S_{n,t}} \right)$$

implying that the aggregate demand is $Y_t^D = \sum_{s \in \mathcal{S}_t} p_{s,t} Y_{s,t}^D$.

Supply side. On each goods market, the aggregate supply $Y_{s,t}^S$ is given by

$$Y_{s,t}^S = \omega_s (Y_{s,t} - \kappa_{s,t} V_{s,t})$$

implying that the aggregate supply is $Y_t^S = \sum_{s \in \mathcal{S}_t} p_{s,t} Y_{s,t}^S$.

Equilibrium prices. Given that $Y_{s,t}^D = Y_{s,t}^S \equiv Y_{s,t}^*$ at the equilibrium, $\forall s$, implying $Y_t^D = Y_t^S \equiv Y_t^*$, the equilibrium prices are deduced from

$$p_{s,t} = \left(\frac{1}{S_{n,t}} \frac{Y_t^*}{Y_{s,t}^*} \right)^{\frac{1}{\sigma}} \quad \forall s \in \mathcal{S}_t$$

Labor market. Using the wage equation, we obtain the following reservation productivity (job destruction condition), hirings (job creation condition) and the dynamic of the marginal job value ($J_{s,t}$) :

$$\begin{aligned} \alpha_{s,t}^r &= \max \left\{ 0; \frac{1}{(1 - \eta_s) p_{s,t} A_{s,t} A_t} \left((1 - \eta_s) b_s + \eta p_{s,t} \kappa_{s,t} \theta_{s,t} - \beta_t (1 - s_{s,t+1}) J_{s,t+1} \right) \right\} \\ \frac{p_{s,t} \kappa_{s,t}}{q(\theta_{s,t})} - \lambda_{s,t} &= \beta_t (1 - s_{s,t+1}) J_{s,t+1} \\ J_{s,t} &= (1 - \eta_s) (p_{s,t} A_{s,t} A_t \tilde{\alpha}_{s,t} - b_s) - \eta_s p_{s,t} \kappa_{s,t} \theta_{s,t} + \beta_t (1 - s_{s,t+1}) J_{s,t+1} \end{aligned}$$

Closure and reopening of a business sector. A recession can lead one sector s to close ($N_{s,t} = 0$) or to be unable to sell ($Y_{s,t} < \kappa_{s,t} V_{s,t}$) in period t . If it is the case, then the number of exchanged varieties is lower than its maximal number, i.e. $\dim(\mathcal{S}_t) < S$. But, at the same time, the entrepreneur's expectations can lead her to reopen in $t + 1$. Therefore, it is necessary to borrow in t from the capitalists an amount of their storable goods to post vacancies at period t in order to restart the activity in $t + 1$. Given that, this sector s has a "negative" net supply ($Y_{s,t}^S = \omega_s (Y_{s,t} - \kappa_{s,t} V_{s,t}) < 0$), there is no sell for sector s in period t . Without any information on the relative price of this goods s in t , this transaction is valued at the price ψ_s in the budget constraint of the capitalist.¹⁷ If capitalists do not exist, firms can not reopen after a period without sells.

¹⁷This shadow price ψ_s is calibrated such that the storable goods of capitalist always respect $B_t > 0$.

3 Quantitative results

In this section, we first present our calibration strategy. We use the workers' flows by diploma and the major features of the "subprime crisis" (the 2008 crisis). This leads us to identify the parameters allowing our model to explain a crisis driven by a common financial shock to each labor market segment.

Given these calibration results, we then use the model to predict the impact of the "COVID-19 crisis" (the 2020 crisis). Taking advantage of our heterogeneous agent model¹⁸ and of the first three months of observed data since the beginning of the lockdown, we propose to reveal the "lockdown shocks" for each skill-segment of the labor market (each sector, or worker skill, being differently affected by the lockdown measures) using our model calibrations. Then, we forecast the recovery. We then focus on two scenarios: one scenario with only one wave of the pandemic which lasts 3 months, and a second with two pandemic waves, of the same magnitude and duration, the second wave being expected to start in October 2020.

3.1 Calibration

The model is calibrated at a monthly rate. Thus the average value for $\beta = 1/(1 + 0.0573)^{1/12}$.¹⁹ For the capitalist preference parameters, we set $\delta = 0.025/12$ and $\nu = 1.7$, which is in the range of the usual retained values between 1.5 and 2. We calibrate the share of this population to represent 2% of the overall population, with a saving rate of 10% (See Saez and Zucman (2014)). This allows us to deduce the steady state values for C^K and B^K and identify A_b .

For the workers, we normalize the average of the aggregate productivity component to unity ($A = 1$). Each "sector" represents the production of a type of worker, being identified by her educational attainment.²⁰ We restrict the Log-normal distributions of α to be the same for each sub-population, with a zero mean and a standard deviation equal to 0.12 as in Krause and Lubik (2007).

Using the data provided by Cairo and Cajner (2016), we have the worker flows based on

¹⁸Prassl et al. (2020) and Fana et al. (2020) have shown that the lockdown measures induced by the COVID-19 have unequal impacts on workers, suggesting that the lockdown shock is worker-skill specific.

¹⁹This value matches the mean discount rate in international data, 5.37% per annum.

²⁰As this characteristic practically does not change after entering the labor market, this segmentation justifies the absence of mobility between "sectors" assumed in our model.

CPS data from January 1976 to January 2014. In order to use a larger sample, we rescale these data so that it will be coherent with the aggregate worker flows computed from 1947 to 2020 using BLS data.²¹

3.1.1 Calibration using first order moments

The first order moments of worker flows used to identify model parameters are in the table 1, where all job finding rates (JFR) are the same as they are not significantly different in average. At the steady state, these moments are linked by the restrictions

$$UR_s = \frac{JSR_s}{JSR_s + JFR_s}.$$

	Less than HS	HS	College	Bach. and more	Aggregate
JFR	0.411	0.411	0.411	0.411	0.411
JSR	0.052	0.029	0.024	0.019	0.024
UR	0.112	0.066	0.055	0.030	0.057
Share in population	8.984%	28.626%	35.406%	26.982%	100%

Table 1: **Worker flows and stocks.** Data comes from Cairo and Cajner (2016) starting from 1976 to 2014 and rescaled by the authors. For the wage per diploma the data comes from BLS and goes from 2000 to 2020. Educational attainment are less than high school diploma (Less than HS), high school diploma (HS), college diploma (College) and bachelor or higher diploma (Bach. and more).

Assuming, as in Den Haan et al. (2000) or Krause and Lubik (2007), that 68% of the separations are exogenous, the job separation rates by skill (JSR_s) give the equilibrium values of α_s^r . Using the job finding rates by skill (JFR_s), we deduce the equilibrium value of θ_s . Applying the definitions of UR_s , we can then deduce V_s at the steady state. Finally, with the Log-normal distribution of α , we deduce $\tilde{\alpha}_s$.

We use the two FOCs of the firm's program with respect to $\theta_{s,t}$ and $\alpha_{s,t}^r$ to identify two parameters in each sector. We choose to identify η_s and $\tilde{b}_s \equiv b_s/(p_s A_s)$ which are thus skill-specific. If we assume that the steady state value of κ_s is proportional to A_s , s.t. $\kappa_s = k A_s$, then we identify η_s as follows:

$$\eta_s = 1 - \frac{k}{q_s(\theta_s)\beta(1 - jsr_s)(\tilde{\alpha}_s - \alpha_s^r)}$$

where k is chosen s.t. $\frac{\sum_s \omega_s N_s \eta_s}{\sum_s \omega_s N_s} = 0.5$, leading to $k = 0.103$. The other FOC allows to

²¹See the Appendix B for more details on the data.

identify $\tilde{b}_s = \frac{b_s}{p_s A_s}$:

$$\tilde{b}_s = \alpha_s^r - \frac{\eta_s}{1 - \eta_s} k \theta_s + \frac{1}{1 - \eta_s} \frac{k}{q(\theta_s)}$$

which leads to a ratio between home production and production in business of $rb_s = \tilde{b}_s / \tilde{\alpha}_s$.

The results of this calibration procedure are reported in table 2

	Less than HS	HS	College	Bach. and more
s_s^{endo}	0.0172	0.0095	0.0079	0.0041
s_s^{exo}	0.0353	0.0198	0.0165	0.0087
$\tilde{\alpha}_s$	1.0119	1.0099	1.0095	1.0085
η_s	0.3967	0.4821	0.4972	0.5533
rb_s	0.9490	0.9417	0.9400	0.9323

Table 2: **Results of the calibration using labor market restrictions.**

3.1.2 Calibration based on the subprime crisis experience

To identify the remaining parameters

$$\Psi_1 = \{\sigma, \xi, \{\tau_s\}_{s=1}^S, \{A_s\}_{s=1}^S, \{\gamma_s\}_{s=1}^S\},$$

with $\dim(\Psi_1) = 2 + 3 \times S$ and $S = 4$, we choose moments that describe the worker flows during the subprime crisis of 2008 (the last crisis, before COVID-19). This allows the model to reveal under which restrictions it can generate a deep crisis.²²

Matching the relative wages. We restrict the set of parameters in order to minimise the distance between the skill-specific relative wage in the model and its empirical counterpart.²³ For each set of parameters $\{\sigma, \{\tau_s\}_{s=1}^S\}$, we restrict the values of $\{A_s\}_{s=1}^S$ such that the model matches the average wages by diploma observed in the US:

$$\frac{w_s^{data}}{\text{mean}(w_s^{data})} = \frac{p_s A_s \Gamma_s}{\sum_{s=1}^4 \tilde{\omega}_s p_s A_s \Gamma_s} \quad \text{with } \Gamma_s = \eta_s (\tilde{\alpha}_s + k \theta_s) + (1 - \eta_s) \tilde{b}_s$$

²²We assume that the economy is initially at its steady state. At date t_0 , the aggregate shock makes the economy deviate from its steady path. In the final date t_1 the economy will converge back to its steady state. We set $T = t_1 - t_0 = 120$: 10 years after the shock, the economy comes back to its steady state.

²³The statistics for wages are the weekly and hourly earnings data from the Current Population Survey, over the period 2000-Q1 to 2020-Q1.

where empirical data are denoted w_s^{data} . Nevertheless, this restriction depends on the equilibrium prices p_s . Therefore, this identifying system is solved using all the general equilibrium restrictions:

$$p_s = \left(\frac{1}{S} \frac{\sum_{s=1}^S p_s \omega_s (Y_s - \kappa_s V_s)}{\omega_s (Y_s - \kappa_s V_s)} \right)^{\frac{1}{\sigma}} \quad \text{with } Y_{s,t} = A_s N_s \tilde{\alpha}_s$$

that gives the consistent relative prices $p_s, \forall s$. This procedure gives a unique solution if we add the normalization $\sum_s \omega_s p_s A_s = 1$ meaning that the average productivity is equal to unity.

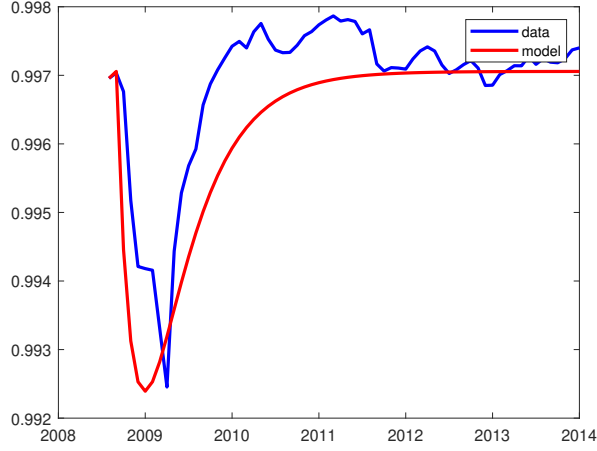
The financial shocks. In order to generate a global financial crisis, we must introduce a common financial shock -that is to say striking all economic players uniformly- able to reproduce the observed depression and recovery in the US labour market. Following Hall (2017), we model this financial shock as a drop in the discount rate, as if this rate included variations in the risk premium. Indeed, the risk premium data exhibited a prominent spike in 2008-09 when it rose way above its historical average during this Great Recession: the difference between the yield on a risky bond (given by 5-Year High Quality Market (HQM) Corporate Bond Spot Rate) and the yield on a Treasury bond of equivalent maturity rose from 0.6 points in January 2007 to 5.45 points in October 2008. In 2008, the expectations of an increase in risks lead the risk premium to rise and thus induce a fall in the discount factor.²⁴ Since the risk premium measures expectations of credit risk and default in the economy, it is an important way to monitor markets to ascertain whether a downturn is expected in the near future. Given that the DMP model is an asset pricing model, these financial expectations in the risk premium are important for the valuation of jobs and thus have a direct impact on hiring and separation decisions. By decreasing the discount factor, the financial crisis reduces the discounted value of expected profits, then instantaneously reducing (increasing) hirings (separations).

Therefore, we assume that the sequence of β_t is given by the following process

$$\beta_t = \rho_b \beta_{t-1} + (1 - \rho_b) \beta - \frac{\epsilon_{b,0}}{\sigma_b^{(t/\mu_b)}}$$

where ρ_b gives the persistence of the AR part of the process, $\epsilon_{b,0}$ the initial size of shock and $\sigma_b^{(t/\mu_b)}$ the chronic of the shocks as a function of $\epsilon_{b,0}$. In order to calibrate $\{\rho_b, \epsilon_{b,0}, \sigma_b, \mu_b\}$, we choose to fit the time series $1/(1 + d_t/P_t)$ where d_t/P_t is the inverse of the price to

²⁴Our reasoning is build on the following simple Euler equation $1 = \beta_t(1 + r_t)$ where r_t is the rate of returns of risky assets.



(a) Blue line: data. Red line: model

Figure 1: **Discount factor.** Parameters values: $\rho_b = 0.85$, $\epsilon_{0,b} = 0.0025$, $\sigma_b = 1.75$ and $\mu_b = 1.5$

dividend ratio based on S&P500 data provided by Hall (2017), from September 2008 to December 2013. The calibrated shock is displayed in figure 1.

The TFP shock. Beyond this direct impact of financial shock on the discount factor, the 2008 crisis is also characterized by a TFP decline: over the period 1947-2019, the annual growth of the US TFP has been 1.23% in average, but it was only -0.72% in 2007, -2.14% in 2008 and -0.46% in 2009, the only 3 consecutive years of negative TFP growth since 2000 (except in 2001, with -0.03% and 2016 with -0.71%).²⁵ Moreover, as it is underlined in Hall (2017), a shock on the discount factor alone is not sufficient to account for the magnitude of the great recessions. Therefore, these two points lead us to introduce a TFP shock that follows:

$$\log(A_t) = \rho_a \log(A_{t-1}) + (1 - \rho_a) \log(A) + \frac{\epsilon_{a,0}}{\sigma_a^{(t/\mu_a)}}$$

with $\Psi_2 = \{\rho_a, \epsilon_{a,0}, \sigma_a, \mu_a\}$, with $\dim(\Psi_2) = 4$.

Matching the dynamics of worker flows by diploma. We identify $\Psi = \{\Psi_1, \Psi_2\}$, with $\dim(\Psi) = 6 + 3 \times S$ and $S = 4$ using $\Phi = \{\{JSR_{s,t}\}_{s=1}^S, \{JFR_{s,t}\}_{s=1}^S, \{UR_{s,t}\}_{s=1}^S\}_{t=t_0}^{t_1}$ where t_0 corresponds to September 2008 and t_1 to December 2013. Given that $\dim(\Phi) > \dim(\Psi)$, this strategy can be interpreted as an informal test of the model. We search Ψ that minimizes the Root Mean Square Error (RMSE) for each time series in Φ . The

²⁵See the data provided by the FED of Saint-Louis:

<https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/>.

results are displayed in Figure 2 and show that the model can match the dynamics of the four labor markets (Less than high school, high school, College, bachelor and more). The peak in unemployment for those with a lower diploma than those issued in high

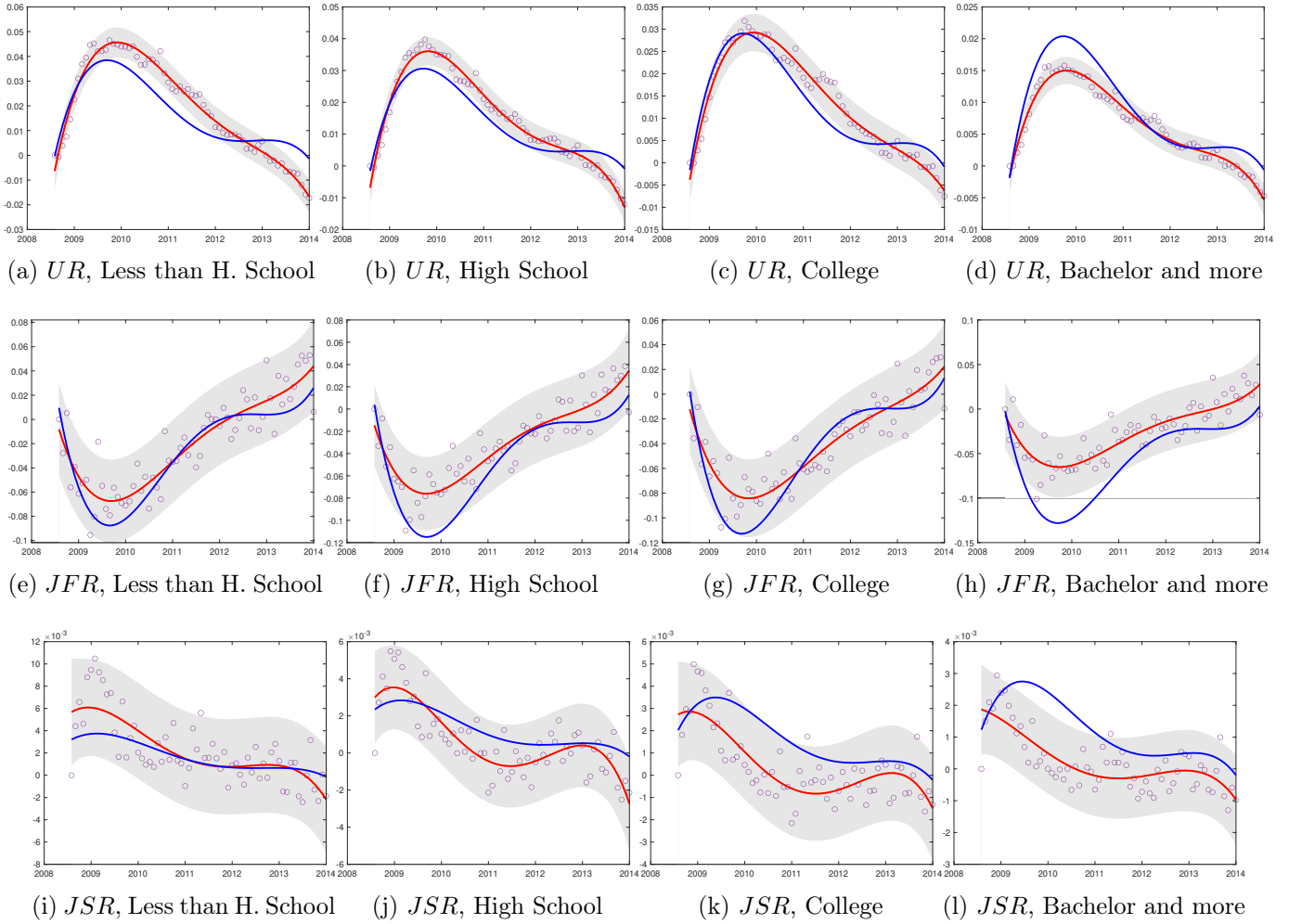


Figure 2: Benchmark calibration: Worker flows and stock by diploma. The circles represent the raw monthly data leading to a smoothed polynomials in red with a confidence bands (95%) in gray. The blue lines are the data generated by the model

schools (less than HS) witnesses a 5 point increase in unemployment rate compared to the 2008 summer level. This rise was only of 3.5 points for those who have graduated from a high school, 3 points for those with a diploma issued by a college, and 1.5 points for those who have obtained a bachelor or more. The model succeeds in reproducing this heterogeneity of opportunities on the labor market. Consistent with the work of Cairo and Cajner (2016), these differences in the adjustment of unemployment rates are due to the greater amplitudes of separations according to the educational attainment: the

less qualified graduates lose their jobs more easily than the more qualified ones, while the chances of finding a job decrease in same proportions for all types of graduates. Therefore, endogenous separations are crucial for explaining heterogeneity in the unemployment dynamics.

The value of the identified parameters are reported in Table 3. The aggregate series

Common Parameters	σ	ρ_a	$\epsilon_{a,0}$	σ_a	μ_a	ξ
	2	0.7	0.0055	1.17	3	0.5
		Less than HS	HS	College	Bach. and more	
Specific Parameters	A_s	0.4855	3.0748	5.2146	8.2714	
	τ_s	1.4	1.5	1.5	1.6	
	γ_s	0.8	0.6	0.5	0.37	
Equilibrium values	p_s	4.9530	1.0742	0.7375	0.6617	
	$p_s A_s$	2.4047	3.3030	3.8456	5.4733	

Table 3: **Results of the calibration.**

generated by the model and their empirical counterparts are displayed in Figure 3: the model generates dynamics of JFR , JSR and UR that are in the confidence interval of the data. Moreover, in accordance with Hall (2017)'s results, the value of jobs fell during this financial crisis. Our benchmark calibration explains half of the observed drop in S&P 500 values.

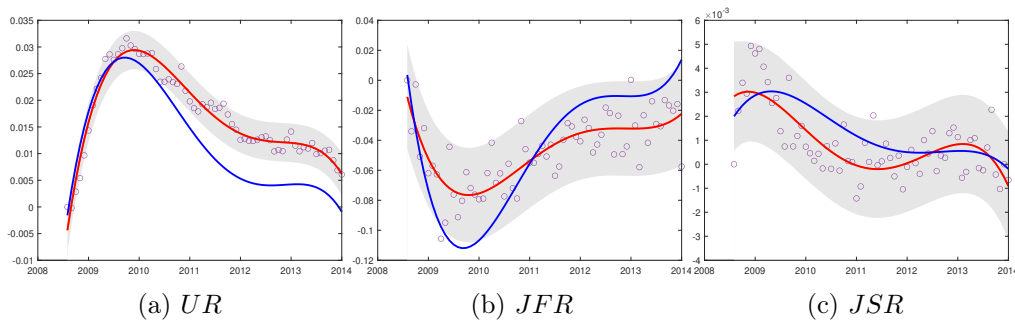


Figure 3: **Benchmark calibration: Aggregates worker flows and stock.** In Panels (a)-(c), the circles represent the raw monthly data leading to a smoothed polynomials in red with a confidence bands (95%) in gray. The blue lines are the data generated by the model.

Despite the absence of persistence of microeconomic shocks, our model goes beyond the usual limits of the DMP model by generating a large endogenous persistence: unemployment comes back to its initial value after 7 years, whereas the shock disappear ap-

proximately 3 years afterward. Moreover, the model is also able to reproduce a different separations' dynamics from the ones present in the productivity. Those results come from the introduction of microeconomic risks and congestion externalities on hirings that are both time varying.

Figure 3 illustrates the accuracy of the results of our model when we compare its predictions to aggregate indicators of the US labor market. The magnitude impact of a crisis, its persistence as well as these contrasted impacts on heterogeneous workers seeming to be correctly reproduced, this model can therefore be used to predict the COVID-19 crisis.

3.2 The COVID-19 crisis in the US

In order to give a prediction of the impact of the COVID-19 crisis, we use two scenarios. The first one presents the one wave scenario of the epidemic in March. The second one, which will represent the two waves scenario, will bend over the case of a surprise outbreak on March and a similar one on October of the same magnitude, duration and depth.

A problem with the evaluation of the COVID-19 crisis impacts comes from the magnitude of the shock hitting each sector. We calibrate at 2 months the duration of crisis for each sector, this duration corresponding to the "strict" lockdown measures (lower bound): as the lockdown was not effective throughout the month of March, this also leads us to differentiate the size of the shock for March. Moreover, the direct impact of the lockdown measures are different across sectors: both the restrictions on the production process as well as the induced demand contraction are sector specific, suggesting that the size shock must be specific to each sector.²⁶ Using our calibrated model and the observations of the US aggregates since February 2020, we then choose to reveal the size of the sector specific shocks that allows the model to replicate the US data known since the beginning of the crisis.

The results are reported in Figure 4. The interesting fact of the data (red lines) is that it already includes a turning point: this suggests that the shock was brutal and strong, but that it is very little persistent, the recovery already being made in May 2020.

The one wave scenario. In the scenario of a single wave, the model reproduces the 12 percentage point increase in US unemployment (see Panel (d) of the Figure 4). This sharp

²⁶Note that our modeling of the restrictions induced by confinement in the form of a shock specific to each sector allows a sparse calibration. It would have been much more complex to calibrate the explicit work restrictions, those relating to consumption, but also the different aids granted to each profession and/or worker.

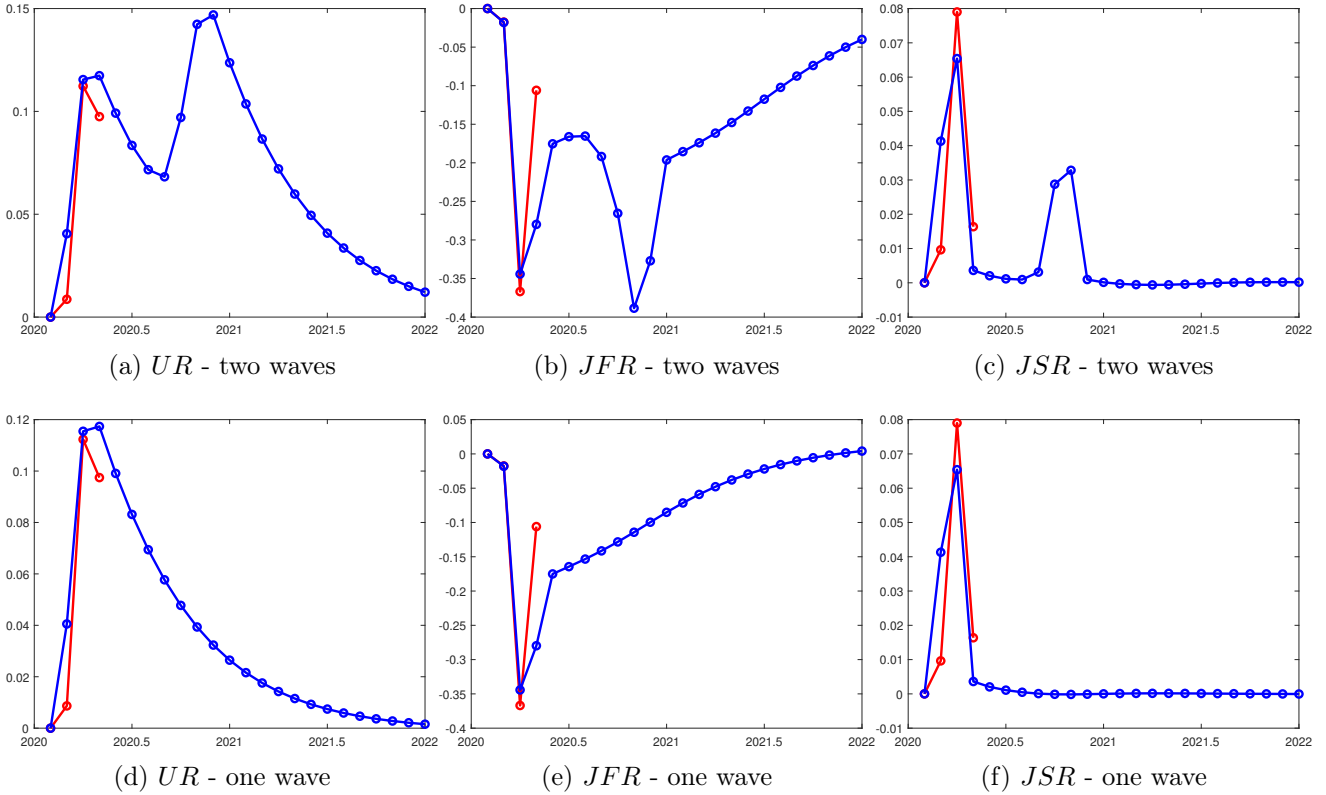


Figure 4: **Aggregate outcomes.** Panels (a)-(c): two waves in March and October. Panels (d)-(f): one wave in March. Red lines: data. Blue lines: model.

rise in unemployment is largely due to the impressive drop in hiring (see Panel (e) of the Figure 4). However, without the very sharp rise in layoffs (see Panel (f) of the Figure 4), the steep increase in the unemployment rate between March and April would not have been possible.²⁷ Panel (a) of Figure 5 displays the contributions of separations and findings in unemployment dynamics. It appears clearly that the initial rise of unemployment is mainly due to separations (95% of the initial jump of unemployment rate), but after three months, the unemployment rate adjustments are driven by the job finding rate. This underlines the importance of congestion externalities introduced in hiring costs in order to generate a sufficiently large persistence in the unemployment dynamics after a recession.

The two waves scenario. Despite the high reactivity of the US labor market, the simulation of a second wave that started in early October shows that unemployment

²⁷Note that with such large variations and persistent in the worker flows, it is no longer possible to use a steady state approximation of unemployment rate $UR_t \approx JSR_t / (JSR_t + JFR_t)$. Hence, the contribution of separations and findings in unemployment dynamics can only be obtained by simulations of counterfactuals.

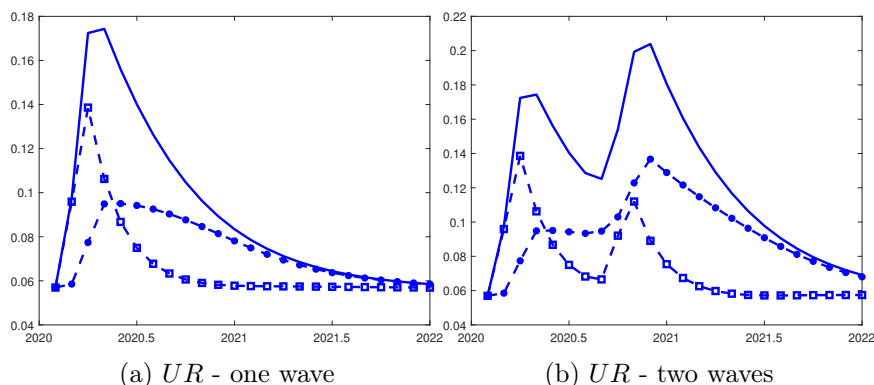


Figure 5: **Contributions of separations and findings in unemployment dynamic.**

The line represents the benchmark case, the dotted line with circles, the counterfactual unemployment rates when *JSR* are at their steady state levels, and the dotted line with squares, the counterfactual unemployment rates when *JFR* are at their steady state levels. Panel (a): two waves in March and October. Panel (b): one wave in March.

could exceed its April peak (see Panel (a) of the Figure 4). Indeed, not having had time to return to its February level after the first wave, a second shock of an amplitude similar to the first wave would cause it to reach a new record at 15% in November 2020. Beyond the amplitude of this peak, this second wave would delay at 2024 the return to the pre-crisis unemployment level. This estimate is more optimistic than the one suggested by Hall and Kudlyak (2020). In fact, with their estimated unemployment rate reduction of 0.5 point per year after a crisis, it would take 20 years for the US economy to go from 15% to 5% unemployment. This difference certainly comes from the very specific nature of the shock linked to COVID-19: very large, but not persistent, characteristics which are not necessarily shared by the past crisis and are more of an economical nature.

Disaggregate outcomes. Behind the evolution of these aggregates, how are the different workers affected? Panel (a) in Figure 6 shows that the shock calibration is consistent with studies showing that the lockdown is more restrictive for the less qualified, or those with the lowest wages. For those with a less than high school diploma, the lockdown reduces by 90% the revenues they generate for firms, while those who own a bachelor degree or more sees the revenues they generate for firms decrease only by 20%. The same results are obtained in the two waves scenario (see Panel (a) of the Figure 7). An important result is displayed in the Panel (b) of Figure 6: in April, the goods produced by the less qualified are no longer sold, and therefore there is no price due to the absence of any transaction. At the same time, the other prices rise, which indicates a strong contraction in supply for all sectors, despite the substitutions that operate towards the sectors which

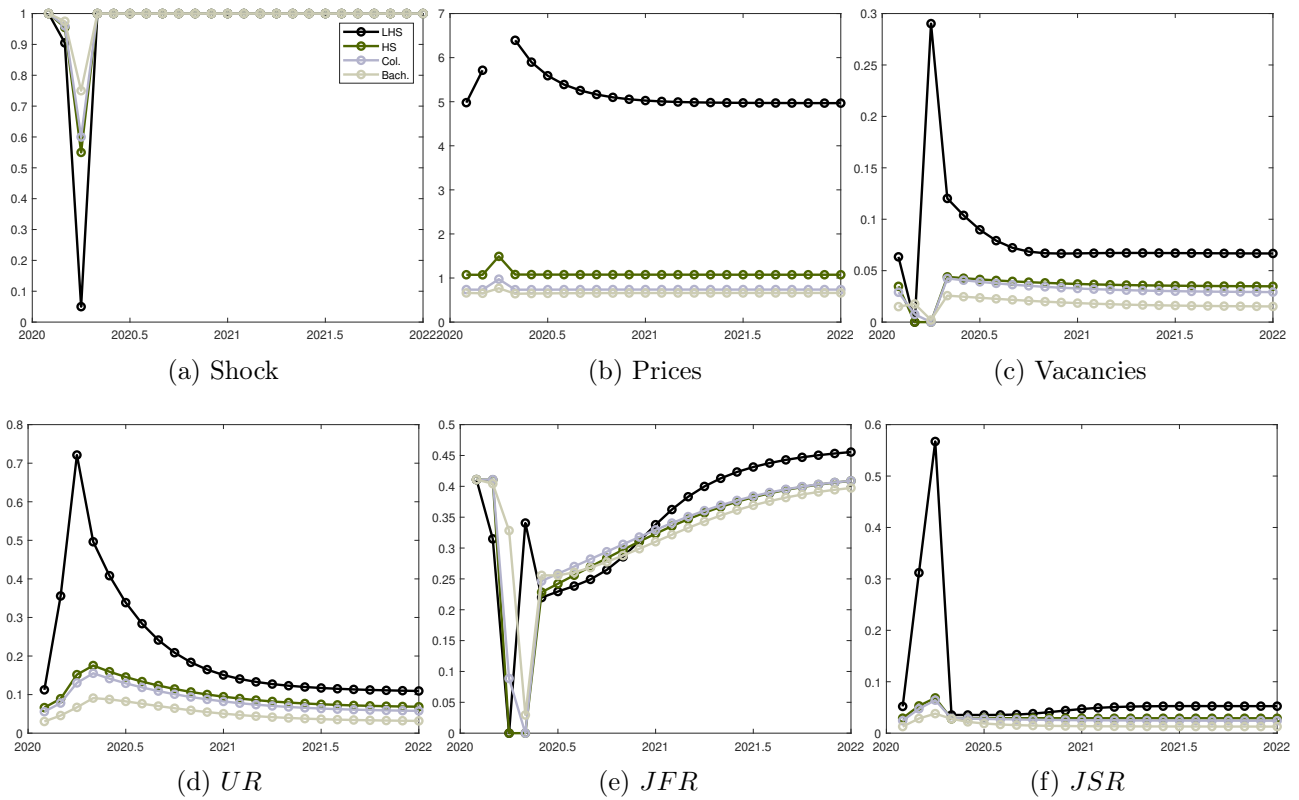


Figure 6: **Disaggregate outcomes: One wave scenario (March)** LHS: Less than High School diploma. HS: High School diploma. Col.: College diploma. Bach.: Bachelor and more diploma.

are the least affected by the restrictions of the lockdown. The sector employing those with the lowest diploma does not close but do not produce enough to supply market in goods for consumption and investment. Its resources as well as those borrowed are directed to the hiring expenditures necessary to prepare the recovery. The Panel (c) of Figure 6 shows that the vacancies directed to workers with less than a high school diploma are very high in April, after being zero in March. This hiring process takes place at a time when the separations reach a maximum level with 58% of the total employment (see Panel (f) of Figure 6). Thus, separations are the main cause of the strong increase in unemployment which requires a very strong adjustment through hirings taking advantage of the recovery (see Panel (d) and (e) of Figure 6). This dynamic contrasts with the one of high school diploma where hiring decisions (Panel (e) of Figure 6), and therefore the opening of vacant positions (Panel (c) of Figure 6), seem to be enough to manage the crisis: during the crisis, the entrepreneur chooses to open no vacancy. Moreover, the fact that separations are below their long run value eased the recover. These more smoothed adjustments are also shared by the labor markets of college and bachelor and more diploma.

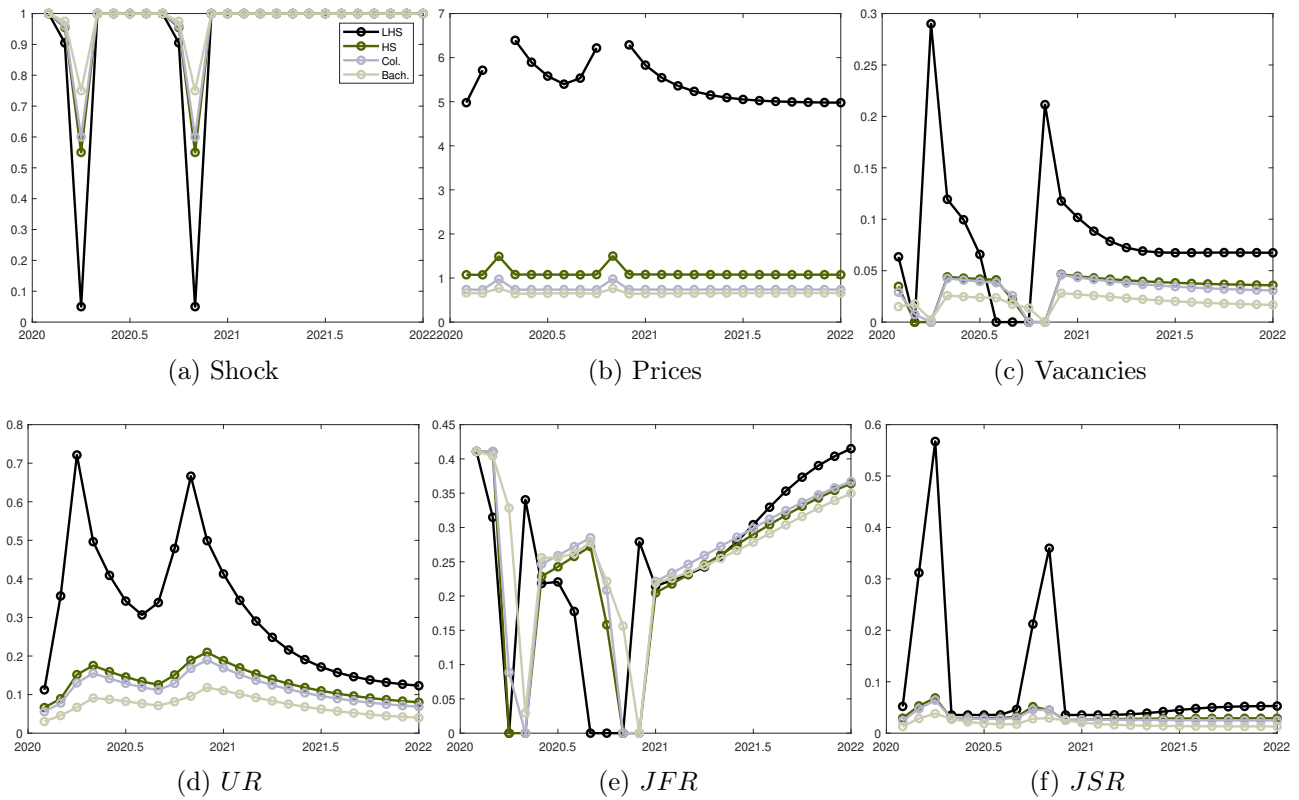


Figure 7: **Disaggregate outcomes: Two waves scenario (March and October)**

LHS: Less than High School diploma. HS: High School diploma. Col.: College diploma. Bach.: Bachelor and more diploma.

In a two-waves scenario, the jobs of those with a less than a high school diploma are very strongly impacted (Figure 7). Moreover, the firms employing these workers do not sell (see Panel (b) of Figure 7), and the large adjustments take place thanks to the quick adjustment of separations (see Panel (f) of Figure 7). Hence, the high variation of separations explains mainly the short term unemployment increase. However, even if separations come back to their steady state values within three months, the persistent low job finding will lead unemployment to last longer (see Panels (c) and (e) of Figure 7).²⁸

²⁸In the Appendix D.1, we present the counterfactuals for the unemployment dynamics of each diploma allowing to give the contribution of job finding and job separation rates in the unemployment rate dynamics.

3.3 The COVID-19 crisis in France

Obviously, as the analysis based on the US data suggests, the impact of a short lockdown, or even two waves scenario, depends crucially on the adjustment speed after the lockdown episode. In order to illustrate this point, we propose to re-calibrate our model on French data.²⁹ Indeed, the French economy is well known for its more rigid labor market compared to the US one, with lower job finding (13.5%) and job separation (1.7%) rates. Even if the job separation rate is lower by 30% in France, the job finding is also lower by 67%. Hence, even if in the French economy separations are not wide, the recovery is stifled by the low and persistent job finding rate, thus suggesting that the two economies might react differently to this sudden lock-down.

Table 4 shows some first interesting results based on the steady state calibration of the French economy. The workers' bargaining power is less dispersed than in the US, in accordance with the lower wage inequalities between the different educational groups. The opportunity cost of employment is also higher in France than in the US, in accordance with the more generous unemployment benefits. Remark that these calibrations, by inducing smaller firm profits in France than in the US, may induce a larger elasticity of the French labor market than the US one to a transitory shock.

	Less than HS	HS	College	Bach. and more
s_s^{endo}	0.0116	0.0064	0.0053	0.0028
s_s^{exo}	0.0241	0.0134	0.0111	0.0060
$\tilde{\alpha}_s$	1.0105	1.0091	1.0088	1.0081
η_s	0.4391	0.4924	0.5045	0.5423
rb_s	0.9756	0.9760	0.9760	0.9751
A_s	1.3457	2.5753	5.8034	7.4356
p_s	2.1976	1.2585	0.6891	0.7697
$p_s A_s$	2.9572	3.2410	3.9991	5.7232

Table 4: **Results of the calibration using French labor market data**

Aggregate outcomes. As for the US, we first look at the implications of our model on the aggregated data as we can compare it to the available data. In the single wave scenario, the model reproduces the 10 percentage points increase of the French unemployment (see Panel (d) of Figure 8). This sharp rise in unemployment is largely explained by the

²⁹We target French worker flows using Hairault et al. (2015) data and relative wages using Insee data. See the Appendix C for more details on the French data.

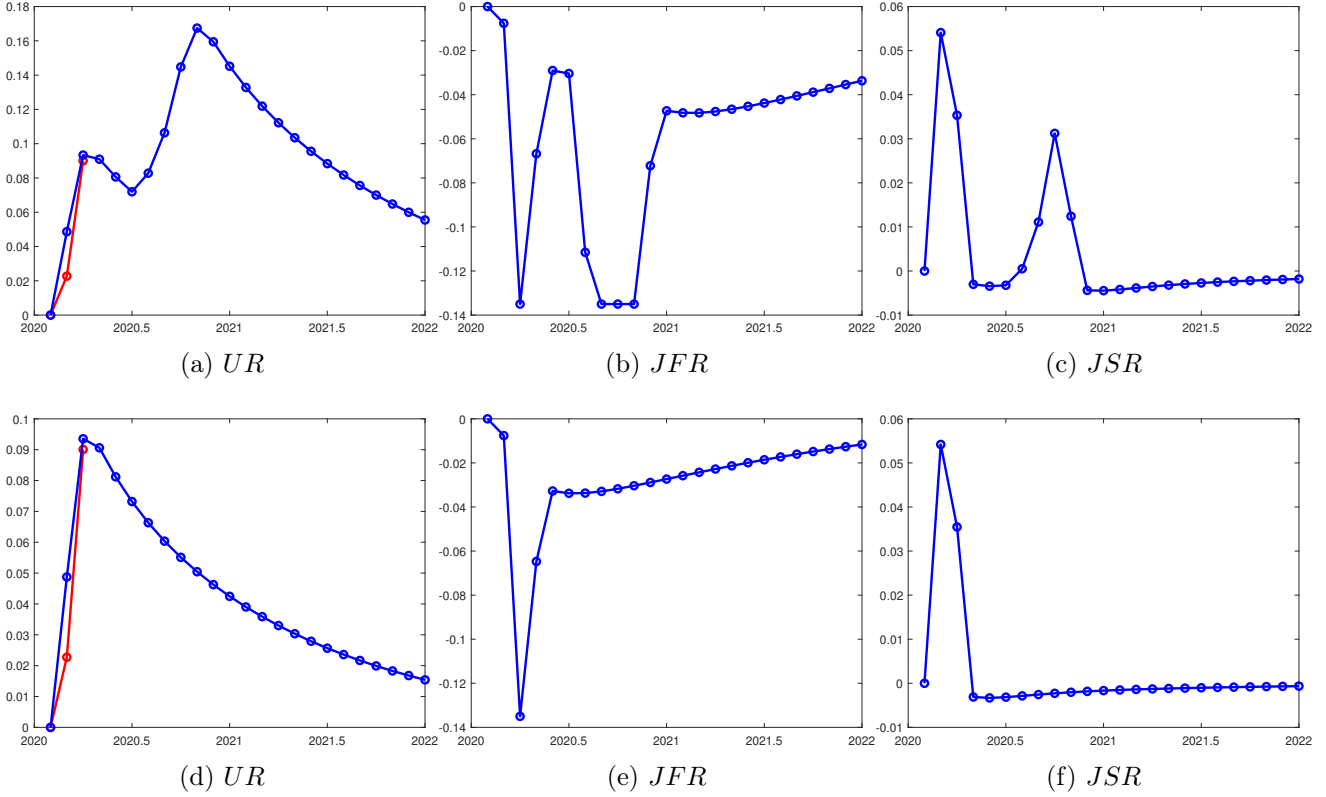


Figure 8: **Aggregate outcomes.** Panels (a)-(c): two waves in March and October. Panels (d)-(f): one wave in March. Red lines: data. Blue lines: model.

important rise in layoffs (see Panel (f) of Figure 8) while its persistence is explained by the total freeze in hiring (see Panel (e) of Figure 8). This is clearly confirmed by Panel (a) of Figure 9 which shows that in the short term the separations determine the amplitude of the increase while the findings affect only the speed of the recovery. The first remarkable difference between France and US is that the job finding rate hit the zero bound. This partly explains why the French unemployment rate does not come back to its steady level by the end only of 2024. This higher persistence is also explained by the second main difference between France and the US: the lower levels of worker flows that mechanically induce a higher persistence.³⁰ This observation is more striking in the case of the two waves scenario. Our forecasts show that unemployment could also exceed its April peak and increase by 17 percentage points in November (see Panel (a) of Figure 8). The big difference with the US comes from a job finding rate that encounters a period of three

³⁰Notice that the unemployment dynamics can be written as the following $AR(1)$ process $u_{t+1} = (1 - jsr - jfr)u_t + jsr$, when the job finding rate (jfr) and the job separation rate (jsr) are assumed to be constant. Therefore, large worker flows ($jsr + jfr$) reduce the coefficient of the $AR(1)$ process and thus the unemployment persistence.

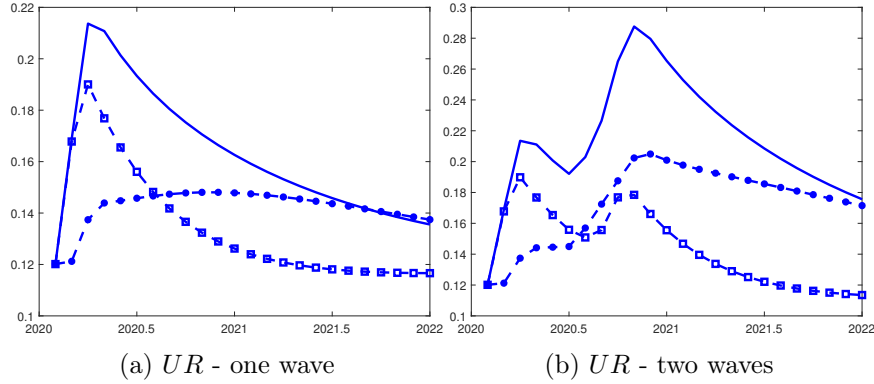


Figure 9: **Contributions of separations and findings in unemployment dynamic.**

The line represents the benchmark case, the dotted line with circles, the counterfactual unemployment rates when JSR are at their steady state levels, and the dotted line with squares, the counterfactual unemployment rates when JFR are at their steady state levels. Panel (a): two waves in March and October. Panel (b): one wave in March.

months at the zero level, making it even harder to come back to the steady state value of unemployment, reached only after 2027, thus highlighting the very large persistence of adjustments on the French labor market.

Disaggregate outcomes. The analysis of the results by sector reveals another important difference between France and US: the size of the French shocks necessary to generate the observed variations of UR , JFR and JSR during the first 3 months of the crisis is much lower than in the US. For the sector employing the less qualified workers, the shock size represents a decline of the firm's marginal revenue of 40%, while in the US economy, it represents a fall of 95%. For the highly qualified, the shock is non existent for the French firms while in US firms they are hit by 25% negative shock.

These differences in the size shocks are in accordance with the different policies implemented in France and in US. Even if the containment restrictions are more stringent in France, they are also accompanied by a large stimulus package (e.g. half of the employees of the private sector have been paid by the French government in May) that aims to rescue the French economy by helping the firms and allowing them to produce and stay open. Hence, the large shock induced by the COVID-19 in US explains why the sector employing those with the lowest diploma do not produce enough to supply market in the US economy while this same sector, which was hit by a smaller shock in France, supplies market even if it stops the hiring process by not opening vacancies. Dampening the shock in France is a necessity because, as this has been underlined in the calibration, the elasticity of the French labor market is larger than in the US one. Therefore, the intervention

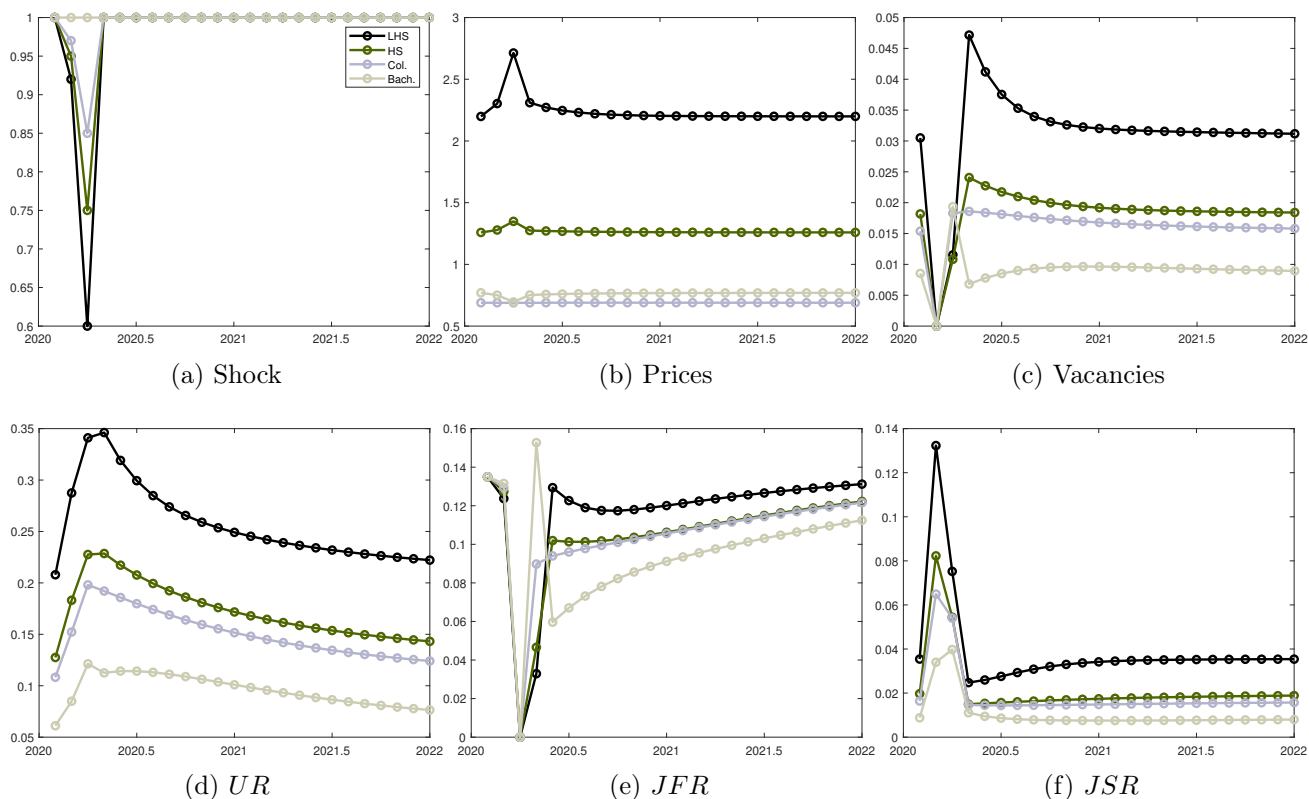


Figure 10: **Disaggregate outcomes: One wave scenario (March)** LHS: Less than High School diploma. HS: High School diploma. Col.: College diploma. Bach.: Bachelor and more diploma.

of the French state ensures the non-explosiveness of unemployment.

In the scenario with two waves (see Figure 11), the slow pace of French adjustments translates into several successive months in which no sector hires (between June and October 2020), which suggests a huge increase in unemployment among young people, leaving school at this time and prospecting for a first job. In this scenario, even those with a bachelor’s degree or more would be hit by an unemployment rate exceeding 15% in October, which has never been seen in France (see Panel (d) of the Figure 11).

4 Conclusion

The objective of this paper is to evaluate the possible impact of the COVID-19 crisis on the US labor market. We show that an extension of the DMP model including general equilibrium can be very useful. Several extensions are introduced: (i) heterogeneity of workers by educational level making it possible to combine heterogeneous adjustments in labor markets hit by different shocks, (ii) endogenous separations making it possible to

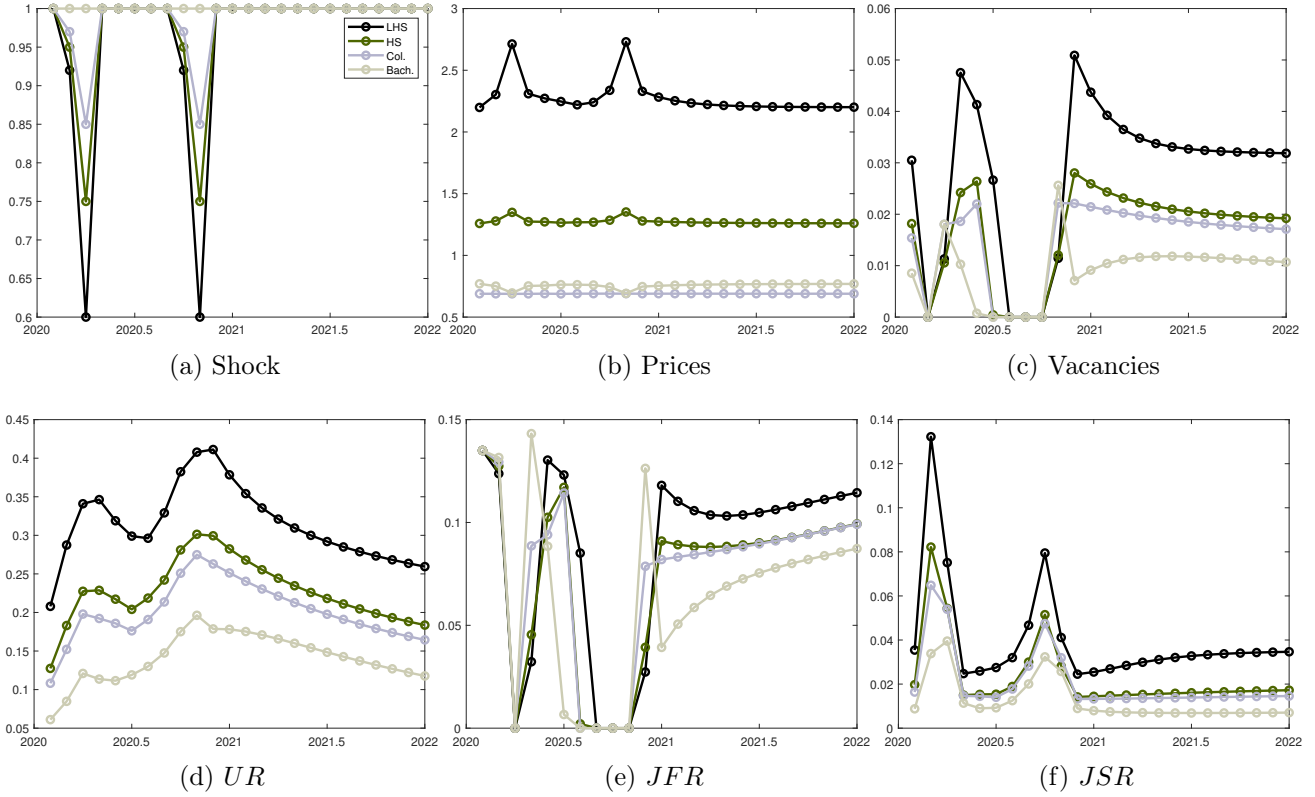


Figure 11: **Disaggregate outcomes: Two waves scenario (March and October)**

LHS: Less than High School diploma. HS: High School diploma. Col.: College diploma. Bach.: Bachelor and more diploma.

account for the sharp increases in unemployment and business closures, *(iii)* time-varying microeconomic risks over the economic cycle, and *(iv)* congestion externalities which may explain the persistence of unemployment during recovery.

First, we show that this model makes it possible to identify the size of the shocks necessary to reproduce the first 3 observed months of the crisis. Second, it predicts a fairly large persistence of unemployment, even if the lockdown period is limited, a return to the pre-crisis situation that can be expected in 2024, even in the case of a second wave of the epidemic that might lead to another lockdown in October 2020. Finally, a comparison with a calibration based on French data, shows that low job finding rates lead to persistent and hence very large effects of the crisis. In the case of the double epidemic wave, the return to the pre-crisis situation could only be expected by 2027, and this even if the lockdown is accompanied by more generous government assistance measures.

This work opens up the field to the question of the evaluation of economic policies that can be studied further in future research using our structural model.

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A FOCs of the firm's problem

The Firm maximizes the following problem :

$$\begin{aligned} \mathcal{V}_{s,t}(N_{s,t}, A_t) &= \max_{V_{s,t}, N_{s,t}, \alpha_{s,t}^r} D_{s,t} + \beta_t \mathcal{V}_{s,t+1}(N_{s,t+1}, A_{t+1}) \\ \text{s.t.} &\begin{cases} D_{s,t} = N_{s,t}(p_{s,t}A_sA_t\tilde{\alpha}_{s,t} - \tilde{w}_{s,t}) - p_{s,t}\kappa_{s,t}V_{s,t} \\ N_{s,t+1} = (1 - s_{s,t+1})(N_{s,t} + q(\theta_{s,t})V_{s,t}) \\ V_{s,t} \geq 0 \end{cases} \quad (\lambda_{s,t}) \end{aligned}$$

The FOC are

$$0 = -p_{s,t}\kappa_{s,t} + q(\theta_{s,t})\beta_t(1 - s_{s,t+1})\frac{\partial \mathcal{V}_{s,t+1}}{\partial N_{s,t+1}} + \lambda_{s,t}q(\theta_{s,t}) \quad (1)$$

$$\begin{aligned} 0 &= \frac{\partial N_{s,t}}{\partial \alpha_{s,t}^r}(p_{s,t}A_sA_t\tilde{\alpha}_{s,t} - \tilde{w}_{s,t}) + N_{s,t} \left(p_{s,t}A_sA_t \frac{\partial \tilde{\alpha}_{s,t}}{\partial \alpha_{s,t}^r} - \frac{\partial \tilde{w}_{s,t}}{\partial \alpha_{s,t}^r} \right) \\ &\quad + \beta_t \frac{\partial \mathcal{V}_{s,t+1}}{\partial N_{s,t+1}} \frac{\partial N_{s,t+1}}{\partial N_{s,t}} \frac{\partial N_{s,t}}{\partial \alpha_{s,t}^r} \end{aligned} \quad (2)$$

$$\frac{\partial \mathcal{V}_{s,t}}{\partial N_{s,t}} = p_{s,t}A_sA_t\tilde{\alpha}_{s,t} - \tilde{w}_{s,t} + \beta_t(1 - s_{s,t+1})\frac{\partial \mathcal{V}_{s,t+1}}{\partial N_{s,t+1}} \quad (3)$$

Knowing that $1 - s_{s,t} = (1 - s_s)(1 - G_s(\alpha_{s,t}^r))$ and using

$$\begin{aligned} \frac{\partial N_{s,t}}{\partial \alpha_{s,t}^r} &= -(1 - s_s)(N_{s,t-1} + q(\theta_{s,t-1})V_{s,t-1})dG_s(\alpha_{s,t}^r) = -(1 - s_s)\frac{N_{s,t}}{1 - s_{s,t}}dG_s(\alpha_{s,t}^r) \\ \frac{\partial \tilde{\alpha}_{s,t}}{\partial \alpha_{s,t}^r} &= \frac{dG_s(\alpha_{s,t}^r)}{1 - G_s(\alpha_{s,t}^r)}(\tilde{\alpha}_{s,t} - \alpha_{s,t}^r) \\ \frac{\partial \tilde{w}_{s,t}}{\partial \alpha_{s,t}^r} &= \frac{dG_s(\alpha_{s,t}^r)}{1 - G_s(\alpha_{s,t}^r)}(\tilde{w}_{s,t} - w_{s,t}(\alpha_{s,t}^r)) \end{aligned}$$

the equation (2) can be rewritten as follows

$$0 = p_{s,t}A_sA_t\alpha_{s,t}^r - w_{s,t}(\alpha_{s,t}^r) + \left(\frac{p_{s,t}\kappa_{s,t}}{q(\theta_{s,t})} - \lambda_{s,t} \right)$$

Using the wage equation, and given that $\alpha \in [0, +\infty)$ when the distribution is Log-Normal, the equilibrium reservation productivity is

$$\alpha_{s,t}^r = \max \left\{ 0; \frac{1}{(1 - \eta_s)p_{s,t}A_sA_t} \left[(1 - \eta_s)b_s(A_t) + \eta p_{s,t}\kappa_{s,t}\theta_{s,t} - \left(\frac{p_{s,t}\kappa_{s,t}}{q(\theta_{s,t})} - \lambda_{s,t} \right) \right] \right\}$$

The first-order conditions of the firm's program lead to the following inter-temporal job creation condition:

$$\frac{p_{s,t}\kappa_{s,t}}{q_s(\theta_{s,t})} - \lambda_{s,t} = \beta_t \left[(1 - s_{s,t+1}) \left(p_{s,t+1}A_sA_{t+1}\tilde{\alpha}_{s,t+1} - \tilde{w}_{s,t+1} + \frac{p_{s,t+1}\kappa_{s,t+1}}{q_s(\theta_{s,t+1})} - \lambda_{s,t+1} \right) \right] \quad (4)$$

The Kuhn-Tucker conditions are given by:

$$q_s(\theta_{s,t})V_{s,t} \geq 0, \quad \lambda_{s,t} \geq 0, \quad \text{and} \quad \lambda_{s,t}q_s(\theta_{s,t})V_{s,t} = 0$$

When $\lambda_{s,t} = 0$, the equilibrium paths are the same than in the DMP model. When $\lambda_t > 0$, we have $V_{s,t} = 0$ and the solution is constrained with $\theta_{s,t} = 0$ and $N_t = (1 - s_s)(1 - G_s(\alpha_{s,t}^r))N_{s,t-1}$.

B Rescaling data

Aggregate data. The macro data for unemployment rate, job finding rate and job separation rate used are constructed from BLS data from 1948 up to today. The monthly employment and unemployment levels data for all people aged 16 and over are seasonally adjusted. To construct worker flows following Adjemian et al. (2019), we use the number of unemployed workers with unemployment duration's of more than five weeks. After dividing the unemployment levels in each month by the sum of unemployment and employment, we obtain monthly series for U_m and U_m^5 (m refers to the monthly frequency), which correspond to the proportion of unemployed individuals and the proportion of individuals unemployed for more than five weeks. The worker flows are given by $JSR_m = \frac{U_{m+1} - U_m^5}{E_m}$ and $JFR_m = \frac{U_m - U_{m+1}^5}{U_m}$.

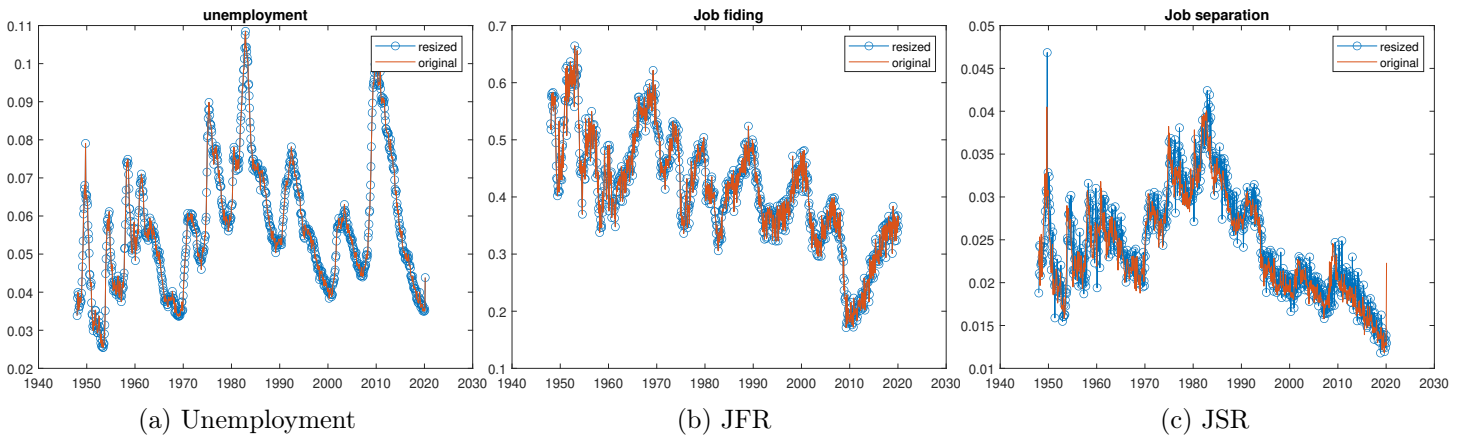
Disaggregate data. We use the constructed data from Cairo and Cajner (2016). Data are based on the CPS basic monthly data from January 1976 to January 2014. They construct the number of short-term (less than 5 weeks) unemployed for each education group that allowed them to compute the heterogeneous job finding and separation rate.

Rescaling method. To be able to use both of data sets we have to rescale them. We assumed that our Aggregate data will be the one unchanged.

First, we construct the artificial Macro unemployment (bur_t , $bjsr_t$ and $bjfr_t$) using the micro data ($ur_{s,t}$, $jsr_{s,t}$ and $jfr_{s,t}$) and the weight of each skill in the economy ω_s : $bur_t = \sum_{s=1}^S \omega_s ur_{s,t}$, $bjsr_t = \sum_{s=1}^S \omega_s jsr_{s,t}$ and $bjfr_t = \sum_{s=1}^S \omega_s jfr_{s,t}$. Then we compute the coefficient of rescaling x^i such that $x_{s,t}^1 = jfr_{s,t}/bjfr_t$, $x_{s,t}^2 = ur_{s,t}/bur_t$ and $x_{s,t}^3 = jsr_{s,t}/bjsr_t$

Second, we reconstruct the micro data to match the macro data (UR , JFR , JSR): $hjsr_{s,t} = x_{s,t}^1 JFR_t$, $hur_{s,t} = x_{s,t}^2 UR_t$ and $hjsr_{s,t} = x_{s,t}^3 JSR_t$.

Finally, to test our estimation we compute the macro data using the rescaled micro data: $hbur_t = \sum_{s=1}^S \omega_s hur_{s,t}$, $hbjfr_t = \sum_{s=1}^S \omega_s hjsr_{s,t}$ and $hbjsr_t = \sum_{s=1}^S \omega_s hjsr_{s,t}$ and compare it the original one (UR , JFR , JSR). We find that the rescaling matches well the data.



(a) Unemployment

(b) JFR

(c) JSR

C French data

Hairault et al. (2015) show that the job finding and the job separation rate are respectively 13.5% and 1.7% which is consistent with a French unemployment rate of 11%. With these macro aggregates, we construct the disaggregate data, assuming that there are identical gaps between workers' flows by diploma and aggregate flows in France and in US. Statistics for these constructed data are reported in table 5.

For the population shares ω_s , we use the French data from Insee indicating the yearly share of employment per diploma in the active population in 2014. This is due to the fact that information on the relative wages is specific to the year 2014. Results are reported in Table 5.

Finally, using Hourly wage per level of education data in 2014 from Insee, we find that the relative average wage per diploma to the average wage (see Table 5).

		Less than HS	HS	College	Bach. and more	Aggregate
<i>JFR</i>	US	0.411	0.411	0.411	0.411	0.411
	France	0.1350	0.1350	0.1350	0.1350	0.1350
<i>JSR</i>	US	0.052	0.029	0.024	0.019	0.024
	France	0.0354	0.0197	0.0164	0.0088	0.017
<i>UR</i>	US	0.112	0.066	0.055	0.030	0.057
	France	0.2079	0.1275	0.1082	0.0611	0.1201
Share in pop.	US	8.984%	28.626%	35.406%	26.982%	100%
	France	17.30%	25%	36.2%	21.5%	100%
Relative wages	US	0.5992	0.8268	0.9536	1.3585	-
	France	0.8642	0.9408	1.1563	1.6628	-

Table 5: Worker flows, population shares and wages:France vs. US

D Contribution of JSR and JFR in UR dynamics by diploma

D.1 US

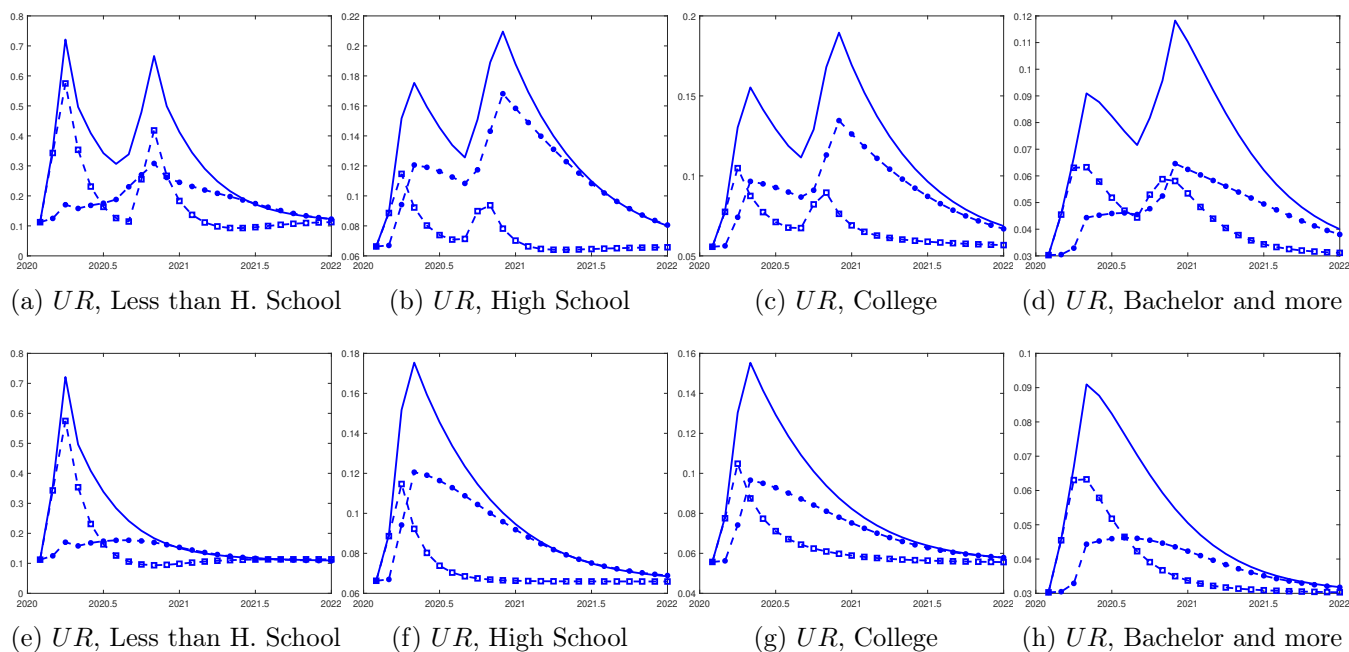


Figure 12: **Contributions of separations and findings in unemployment dynamic.**

The line represents the benchmark case, the dotted line with circles, the counterfactual unemployment rates when JSR are at their steady state levels, and the dotted line with squares, the counterfactual unemployment rates when JFR are at their steady state levels. Panel (a): two waves in March and October. Panel (b): one wave in March.

D.2 France

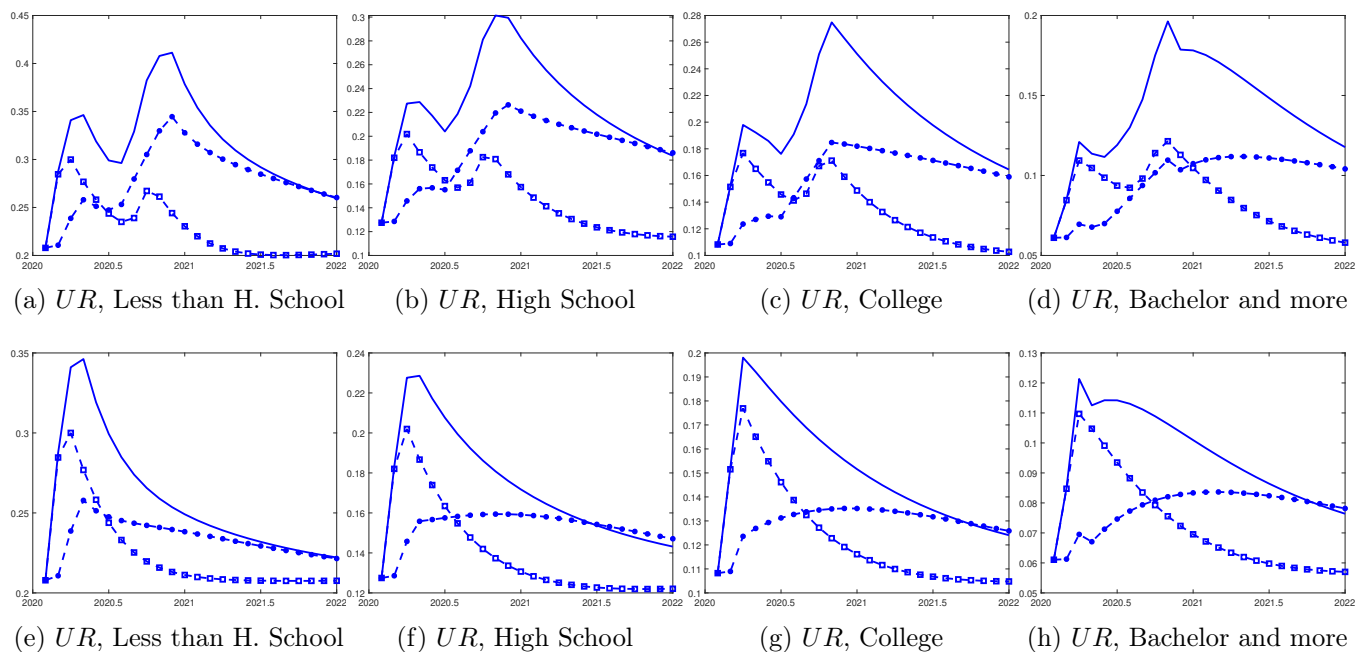


Figure 13: Contributions of separations and findings in unemployment dynamic.

The line represents the benchmark case, the dotted line with circles, the counterfactual unemployment rates when *JSR* are at their steady state levels, and the dotted line with squares, the counterfactual unemployment rates when *JFR* are at their steady state levels. Panel (a): two waves in March and October. Panel (b): one wave in March.