Skill Loss during Unemployment and the Scarring Effects of the COVID-19 Pandemic

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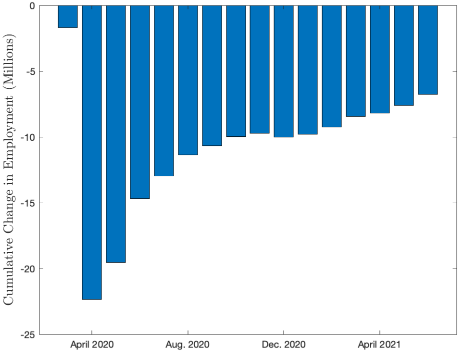
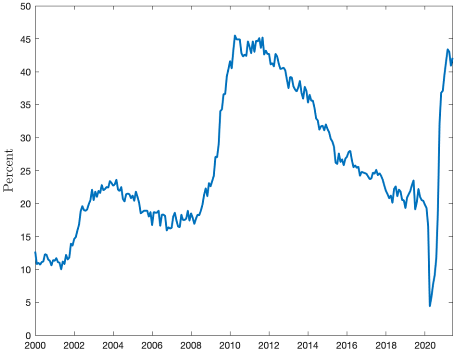
Introduction

- The economic costs of COVID-19 have been extraordinary



Introduction

- Long-term unemployment is at historic levels



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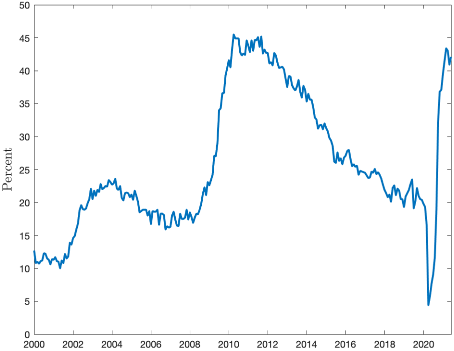


- Empirical evidence, workers lose skills while unemployed

Introduction

- Long-term unemployment is at historic levels

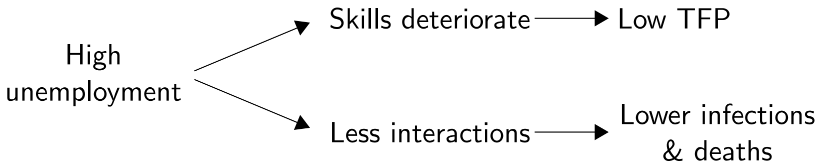
- Empirical evidence, workers lose skills while unemployed

- Potential for large scarring effects due to skill loss

"Moreover, the longer the downturn lasts, the greater the **potential for longer-term damage** from permanent job loss and business closures. Long periods of unemployment can **erode workers' skills** and hurt their future job prospects." – Jerome H. Powell

Questions

- Effects of a pandemic on unemployment, TFP, and health outcomes?
- Impact of job separations at onset of a pandemic on TFP?
- Optimal policy, given conflicting externalities?



What we do

- Integrate canonical SIR framework (Kermack and McKendrick, 1927) into a search and matching model
- Key ingredient: workers lose skills while unemployed
- Calibrate the model to quantify the effects of COVID-19 on
  - Unemployment
  - TFP
  - Health outcomes
- Three month lockdown
- Social planner's problem

Findings

- Quantitative results

	Baseline	Lockdown	Efficient
Increase in unemployment (PP)	3.8	7.6	2.5
Decline in TFP	0.44%	0.56%	0.88%
TFP loss rel. to typical recession	39%	50%	78%

- Planner limits job creation, not to the extent caused by a lockdown

- Skill composition externality is sizeable

Related literature

- **Labor markets and pandemics**: Kapička and Rupert (2020), Gregory et al. (2020), Graham and Ozbilgin (2021), Birinci et al. (2021), Petrosky-Nadeau and Valletta (2020)
- **Integrating the SIR framework into macro**: Atkesson (2020), Eichenbaum et al. (2021), Garibaldi et al. (2020)
- **Optimal policy during a pandemic**: Bethune and Korinek (2020), Farboodi et al. (2021)
- **Loss of skill during unemployment**: Ortego-Marti (2017, 2020), Laureys (2020), Heathcote et al. (2020)

Environment

Time, agents, and preferences

- Time is discrete and indexed by $t \in \mathbb{N}_0$
- Agents
  - Workers: initial population normalized to 1
  - Firms: a large measure
- Preferences
  - Risk-neutral
  - Discount factor $\beta \in (0, 1)$

Workers

- Workers categorized by
  - Employment status: $\{\text{unemployed}, \text{employed}\}$
  - Skill level: $\{\text{low skill } (L), \text{high skill } (H)\}$
  - Health status: $\{\text{susceptible } (S), \text{infected } (I), \text{recovered } (R)\}$

- A measure μ of workers leave/enter the labor force each period
  - Entrants are unemployed, high skill, and susceptible

Health statuses

- Susceptible (S): not yet infected
- Infected (I): infected but not yet recovered or deceased
- Recovered (R): recovered and immune from further infection
- Deceased (D)

Health statuses

- Susceptible (S): not yet infected
- Infected (I): infected but not yet recovered or deceased
- Recovered (R): recovered and immune from further infection
- Deceased (D)
- Transition probabilities
  - $S \rightarrow I$
    - Unemployed: $\pi_t^{UI} = \pi^U \overbrace{I_t}^{\text{Stock of infected workers}}$
    - Employed: $\pi_t^{EI} = \pi^E I_t$
    - $\pi^U < \pi^E$
  - $I \rightarrow R$: π_R
  - $I \rightarrow D$: π_D

Skills and technology

- Skill indexed by $\chi \in \{L, H\}$: low (L) and high (H)
- Infected workers do not produce output
- Productivity of susceptible and recovered workers:
  - High skill: y
  - Low skill: δy with $\delta \in (0, 1)$
- Unemployed workers receive b each period

Skill loss

- High skill workers are susceptible to skill loss
  - Unemployed
  - Employed and infected
- Skill loss occurs with probability σ
- Loss of skill is permanent

The labor market

- Search frictions: Workers search for jobs, firms search for applicants
- Matching technology: $M_t = m(U_t, V_t)$
  - U_t: stock of unemployed workers who are *not* infected
  - V_t: stock of vacancies
- Vacancy posting cost: $k > 0$
- Labor market is unsegmented, firms meet workers of either
  - Skill level
  - Health status (susceptible/recovered)
- Jobs destroyed w/ exogenous probability s

Equilibrium

Bellman equations: Pre-Pandemic steady-state

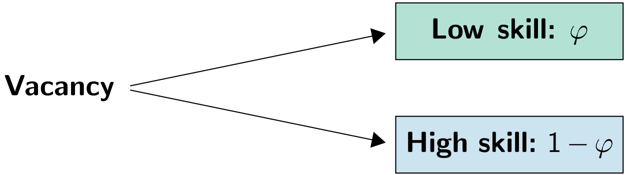
- Unemployed low skill workers

$$U^L = b + \underbrace{\bar{\beta}}_{\beta(1-\mu)} \Big\{ \overbrace{\underbrace{f(\theta)}_{V/U}}^{\text{Pr. to meet a firm}} W^L + (1 - f(\theta)) U^L \Big\}$$

- Unemployed high skill workers

$$U^H = b + \bar{\beta}\Big\{ f(\theta) W^H + \big(1 - f(\theta)\big)\big[\underbrace{\sigma U^L + (1-\sigma) U^H}_{\text{Skill loss}}\big]\Big\}$$

Value of a vacancy



Pre-Pandemic

- Wages determined through Nash-bargaining

$$w^{\chi} = \arg\max \left[W^{\chi} - U^{\chi}\right]^{\eta} \left[J^{\chi}\right]^{1-\eta}$$

- Free entry of firms → job creation condition

$$\frac{k}{q(\theta)} = \bar{\beta}(1-\eta)\left[\varphi F^{L} + (1-\varphi)F^{H}\right]$$

  - φ: (endogenous) fraction of unemployed with low skills
  - F^{χ}: total surplus of a match with type χ worker

- **Inefficiency to keep in mind**
  - Firms do not internalize that job creation affects skill composition (Laureys, 2020)

Steady-state characterization

- Steady-state with $\theta > 0$ exists if $\delta y > b$, k not "too large"
- The steady-state may not be unique (Pissarides, 1992)
  - Firms create more jobs
    $\rightarrow$ skill composition improves
    $\rightarrow$ if effect is strong, RHS of JC condition may be upward sloping
  - Occurs only under extreme parameter values

Value of unemp. during pandemic

- Low skill and susceptible

$$U_t^{LS} = b + \bar{\beta}\Big\{ \underbrace{f(\theta_t)(1-\pi_t^{UI})W_{t+1}^{LS}}_{\text{Become employed}} + \overbrace{\pi_t^{UI}U_{t+1}^{LI}}^{\text{Infected}} + \underbrace{\big(1-f(\theta_t)\big)(1-\pi_t^{UI})U_{t+1}^{LS}}_{\text{Remain susceptible}} \Big\}$$

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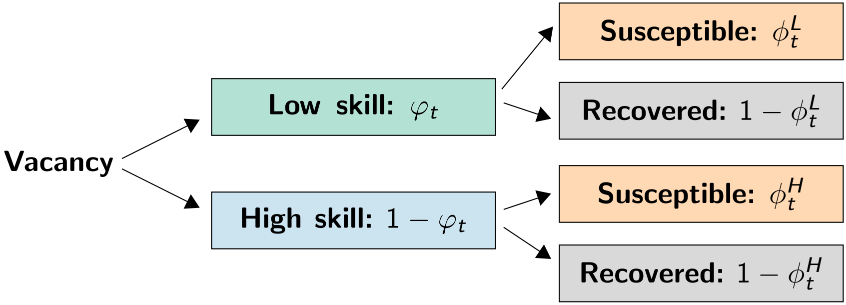
- High skill and susceptible

$$U_t^{HS} = b + \bar{\beta}\{ \underbrace{f(\theta_t)(1-\pi_t^{UI})W_{t+1}^{HS}}_{\text{Become employed}} + \overbrace{\sigma[\pi_t^{UI}U_{t+1}^{LI} + (1-f(\theta_t))(1-\pi_t^{UI})U_{t+1}^{LS}]}^{\text{Skill loss + infection risk}}$$

$$+ \underbrace{(1-\sigma)[\pi_t^{UI}U_{t+1}^{HI} + (1-f(\theta_t))(1-\pi_t^{UI})U_{t+1}^{HS}]}_{\text{Remain high-skilled + infection risk}} \}$$

Job creation during a pandemic

- New layer of heterogeneity among workers: health status



Job creation during a pandemic

$$\frac{k}{q(\theta_t)} = \bar{\beta}(1-\eta)\Big\{ \overbrace{\varphi_t[\underbrace{\phi_t^L(1-\pi_t^{UI})F_{t+1}^{LS}}_{\text{Susceptible}} + \underbrace{(1-\phi_t^L)F_{t+1}^{LR}}_{\text{Recovered}}]}^{\text{Meet a low skill worker}} +$$

$$\overbrace{(1-\varphi_t)[\underbrace{\phi_t^H(1-\pi_t^{UI})F_{t+1}^{HS}}_{\text{Susceptible}} + \underbrace{(1-\phi_t^H)F_{t+1}^{HR}}_{\text{Recovered}}]}^{\text{Meet a high skill worker}} \Big\}$$

- ϕ_t^χ: Fraction of *susceptible* job seekers of skill level χ
- $1-\pi_t^{UI}$: Probability susceptible worker does not become infected

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- ϕ_t^χ: Fraction of *susceptible* job seekers of skill level χ
- $1-\pi_t^{UI}$: Probability susceptible worker does not become infected
- As infections rise, π_t^{UI} and π_t^{EI} increase...
  - $\rightarrow$ more difficult to hire susceptible workers
  - $\rightarrow$ susceptible employees more likely to become infected

Quantitative analysis

Calibration: preliminaries

- Unit of time: one week
- Discount factor: $\beta = 0.99^{1/52}$
- Separation probability: $s = 0.035/(52/12)$
- Average time in labor force: 40 years
- Labor productivity (high skill): $y = 1$
- Ratio of b to average wages $= 0.71$ (Hall and Milgrom, 2008)

Calibration: the labor market

- Cobb-Douglas matching technology
  - Matching efficiency matches job-finding rate of 0.45/(52/12)
  - Elasticity w.r.t. unemployed $= 0.5$ (Petrongolo and Pissarides, 2001)
- Vacancy posting cost targets $\theta = 1$
- Hosios (1990) condition: $\eta = 0.5$

Calibration: skill loss parameters

- Loss of skill parameters $\{\sigma, \delta\}$
  - Probability of skill loss: $\sigma = 1/13$
  - δ to match effects of unemployment duration on wages

Calibration: health parameters

- Following Eichenbaum et al. (2020)
  - Pr. of recovery: $\pi_R = 0.385$
  - Pr. of death: $\pi_D = 0.0039$

- Infection rates π^U, π^E follow Kapička and Rupert (2020)
  - Relative amount of interactions between unemployed and employed
  - Two-thirds of the population is eventually infected and recovered

Parameter values

Parameter	Definition	Value
β	Discount factor	0.9998
y	Productivity of high-skill workers	1.0000
s	Separation probability	0.0081
μ	Probability of exiting the labor force	4.8×10^{-4}
A	Matching efficiency	0.1038
α	Elasticity of the matching function	0.5000
η	Worker's bargaining power	0.5000
σ	Probability of skill loss	0.0769
δ	Productivity of low-skill workers	0.7250
k	Vacancy posting cost	0.3047
b	Value of unemployment	0.5203
π_D	Probability of death from infection	0.0039
π_R	Probability of recovery	0.3850
π^U	Infection exposure of unemployed workers	0.1953
π^E	Infection exposure of employed workers	0.6783

Baseline results

Initiating a pandemic

- Begin with the economy in the pre-pandemic steady-state
  - Population is normalized to 1 $\rightarrow$ 0.001% become infected

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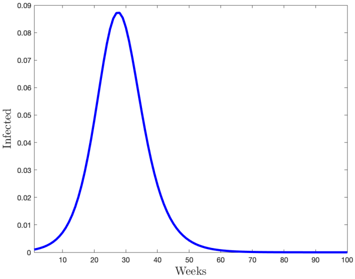
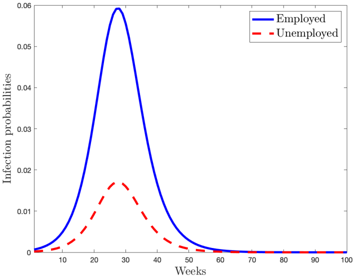
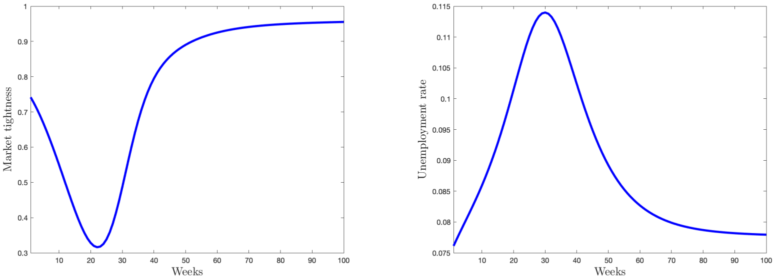


(a) Infections



(b) Infection probabilities

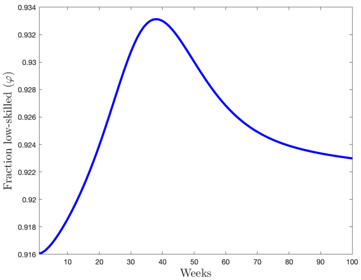
Unemployment during a pandemic



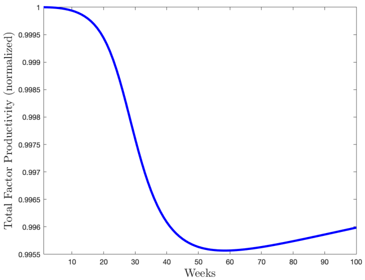
(a) Market tightness

(b) Unemployment

Scarring effects of a pandemic



(a) Composition of the unemployed



(b) TFP

- Sizable TFP losses from skill depreciation alone
  - TFP loss relative to typical recession $\approx$ 39%

Three-month lockdown

Simulating a lockdown

- Separation probability increases from $s = 0.0081$ to $s = 0.0173$
  - Remains at elevated level for 3 months

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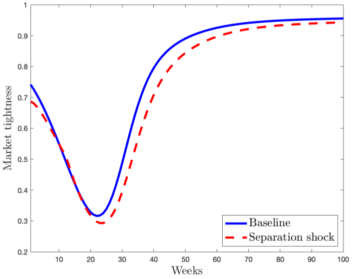

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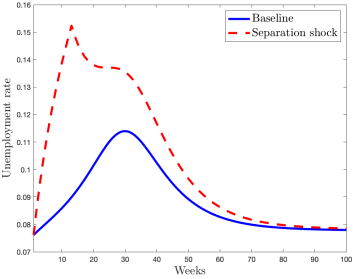
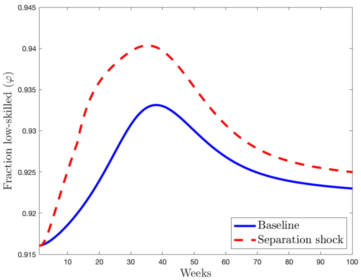


(b) Unemployment

Lasting effects of a lockdown



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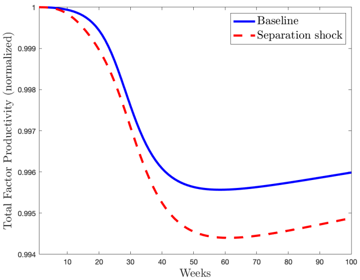


(b) TFP

- Large TFP losses from a lockdown and skill depreciation
  - TFP loss relative to typical recession $\approx 50\%$

Optimal allocations

Planner's problem

- Planner maximizes present-discounted value of net output
  - Controls: market tightness and match formation
- Key tradeoff:
  - Infection externalities (Kapička and Rupert, 2020)
  - Productivity losses

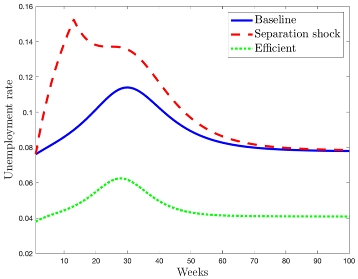
Infection externality

- Social value of a low skill, unemployed, and infected worker:

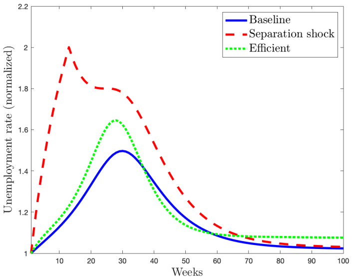
$$\lambda_t^{LI} = b + \bar{\beta}\{\underbrace{(1-\pi_R-\pi_D)\lambda_{t+1}^{LI}}_{\text{Remain infected}} + \overbrace{\pi_R\lambda_{t+1}^{LR}}^{\text{Recover}}\} - \underbrace{\bar{\beta}\Psi_t}_{\text{Infection externality}}$$

- Infection externality captures the effect of an additional infected worker on…
  - Susceptible workers becoming infected
  - High skill workers who are more exposed to skill loss shocks

Optimal unemployment

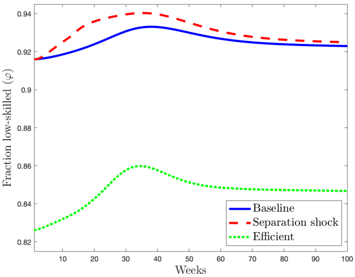


(a) Aggregate unemployment



(b) Normalized unemployment

Skill composition



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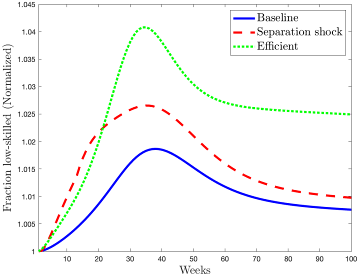
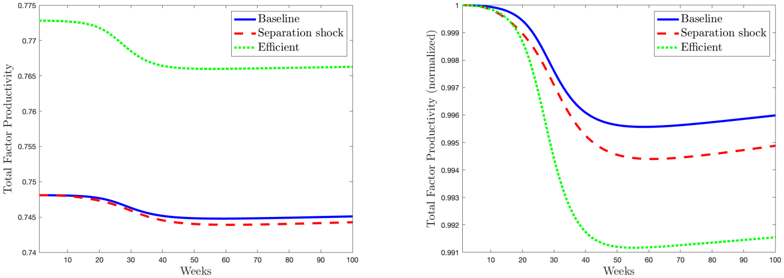


(b) Normalized composition

TFP



(a) Levels of TFP (b) Normalized TFP

- Sizable TFP losses from skills depreciation alone
  - TFP loss relative to typical recession $\approx$ 78%

Conclusion

Conclusion

- Health and economic costs of COVID-19 have been substantial
- Workers lose skills during unemployment
  - Economic scarring effects likely to be substantial
- A theory integrating SIR framework into a search and matching framework in which workers lose skills during unemployment
- Significant decline in TFP due to skill loss
  - Lockdown causes $\approx$ 50% of typical productivity losses in recessions
- Optimal policy involves higher amount of job creation