Scarring Body and Mind: The Long-Term Belief-Scarring Effects of COVID-19

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Recent US Experience

- Economic upheaval typically has long-lived consequences: Depression (Nagel-Malmendier), WWII, financial crisis and secular stagnation.
- What long-term consequences will Covid pandemic have?
- We need theory to predict structural changes.
- Once a vaccine comes, why wouldn't normal return?
  because we learned something and changed our behavior.
- How can we measure and quantify the effect of the knowledge we've gained?
- Solution: Treat agents like econometricians, estimate the change in beliefs from tail realizations, feed updated distributions into an economic/financial model.

Main finding: **Long-term costs are many times larger than economic loss during the pandemic.**

Main Mechanism

- No one knows the true distribution of aggregate shocks
  $\rightarrow$ Re-estimate beliefs as new data arrives

- **Estimation of beliefs:**
  $\rightarrow$ Non-parametric approach to estimation
  $\rightarrow$ Flexible, avoid distributional assumptions, tail risk vs uncertainty
  $\rightarrow$ Use observed macro data, empirical discipline

- **Tail events:** (e.g. the Great Recession)
  $\rightarrow$ large changes in beliefs, in tail probabilities
  $\rightarrow$ these changes are long-lived, even if the underlying shocks are iid

- **Standard SEIR & macroeconomic framework:**
  $\rightarrow$ Quantitatively successful in explaining the post-fin crisis [1]KVV, forthcoming) $\rightarrow$ Consistent with financial market data and popular narratives

Outline

1. Belief formation
2. Epidemiological and economic environment
3. Calibration, COVID scenarios, quantitative results
4. Analysis & Robustness

Belief formation

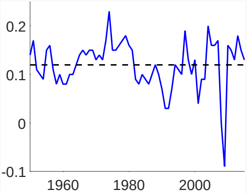
Belief Formation

- Consider an iid shock, ϕ_t, with unknown distribution g
- Information set: finite history of shock realizations $\{\phi_{t-s}\}_{s=0}^{n_t-1}$
- **Goal:** a flexible specification that can capture tail risk
- We use a non-parametric estimator: the Gaussian kernel density

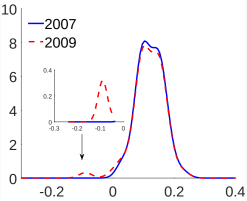
$$\hat{g}_t(x) = \frac{1}{n_t \kappa} \sum_{s=0}^{n_t-1} \Omega\left(\frac{x - \phi_{t-s}}{\kappa}\right)$$

- **Beliefs are martingales:** $\mathbb{E}_t[\hat{g}_{t+j} | \mathcal{I}_t] \approx \hat{g}_t \rightarrow$ **Persistence**

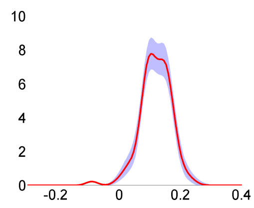
Example: How Return Distribution Changed in ‘09



(a) Capital Return Time Teries



(b) Distribution (before/after)



(c) Future Distributions

Tail events $\rightarrow$ persistent belief changes (even without future crises)

Source: Operating surplus plus holding gains for US corporate business, Flow of Funds

Last panel: Mean and 2-std dev bands for $\hat{g}_{2039}$, drawing from $\hat{g}_{2007}$

Economic Model: Existing Ingredients

Epidemiology Model

SEIR model, $\tilde{t}$ is daily (Atkeson (2020), Wang et al (2020), many).

- Susceptible: $S(\tilde{t}+1) = S(\tilde{t}) - \beta_{It} S(\tilde{t}) I(\tilde{t})/N$
- Exposed: $E(\tilde{t}+1) = E(\tilde{t}) + \beta_{It} S(\tilde{t}) I(\tilde{t})/N - \sigma_E E(\tilde{t})$
- Infected: $I(\tilde{t}+1) = I(\tilde{t}) + \sigma_E E(\tilde{t}) - \gamma_I I(\tilde{t})$
- Recovered / Dead: $D(\tilde{t}+1) = D(\tilde{t}) + \gamma_I I(\tilde{t})$

- Policy determines contact rate $\beta_{It} = \gamma_I \times min(R_0, max(R_{min}, R_0 - \zeta * \Delta I_t))$. lagged infection change ΔI_t is avg $I(t-(15-30))$ - avg$I(t-(31-45))$.
- Shutdowns, which reduce β_I, also idle capital: $K_t^- = \vartheta * (R_0 - \gamma_I \beta_{It})$.
- Idle capital depreciates at $\tilde{\delta}$ (changes in pref.s, rules, accelerated obsolescence)

Takeaway: Disease tiggers temporary shutdowns and permanent obsolescence of capital.

Economic Model

From Gourio (2012, 2013), annual frequency t

- **Preferences:**
  - Representative HH with Epstein-Zin preferences over $C_t - \frac{L_t^{1+\gamma}}{1+\gamma}$
- **Production:** $y_{it} = z_t(\phi_t \hat{k}_{it})^\alpha l_{it}^{1-\alpha}$
  - ϕ_t : obsolescence shock to capital
  - z_t : temporary productivity shock ($z_t = \phi_t^\nu$ for simplicity)
  - Law of motion $\hat{k}_{it+1} = k_{it}(1-\delta) + x_{it}$
- **Firm Credit and Labor Markets:**
  - Firms borrow with 1-period defaultable debt (Eaton-Gersovitz, 1981)
  - Idiosyncratic shocks (iid) $\rightarrow$ positive default in equilibrium
  - Default feedback: Triggers more capital depreciation.
- **Obsolescence**: $\ln \phi_t = \ln \tilde{\phi}_t + \kappa_0 d_t^{1-\varpi}$
  - $\tilde{\phi}_t$: direct effects of disease/shutdown, $\tilde{\phi}_t \sim g(\cdot)$
  - d_t: default rate, amplifies obsolescence

Model: Beliefs and Prices

- **Beliefs :**
  - Distribution of aggregate shocks g unknown to all agents
  - At each date, observe $\{\tilde{\phi}_1, \ldots, \tilde{\phi}_t\}$
  - Gaussian kernel density estimator $\rightarrow$ $\hat{g}_t$

- Firm cost of capital:

$$q_{it} = E_t \left[M_{t+1} \left(\left(1 - F\left(\underline{\nu}_{it+1} \right) \right) + \theta h \left(\underline{\nu}_{it+1} \right) R^k_{t+1} \right) \right]$$

Quantitative Results

Estimating the history of the depreciation shock:

$$\phi_t = \frac{K_t}{\hat{K}_t} = \frac{\text{Effective capital}}{\text{Yesterday's effective capital} + \text{Investment}}$$

Data: Non-financial assets of US Corporate Business (Flow of Funds)

- Commercial real estate ($\sim 55\%$), equipment and software
- Market value $\rightarrow$ Effective capital
- Historical cost $\rightarrow$ Investment

$\Rightarrow$ **Map ϕ_t to observed data**

$$\phi_t = \frac{K_t}{\hat{K}_t} = \left(\frac{P_t^k K_t}{P_{t-1}^k \hat{K}_t}\right)\left(\frac{PINDX_{t-1}^k}{PINDX_t^k}\right)$$

- Historical default rates $\rightarrow$ Recover $d_t, \tilde{\phi}_t$

Calibration

Preferences	β	0.95	Discount factor
	η	10	Risk aversion
	ψ	0.50	1/Intertemporal elasticity of substitution
	γ	1.50	1/Frisch elasticity
	ζ	1	Labor disutility
Technology	α	0.40	Capital share
	ν	0.10	Elasticity of temporary shock
	δ	0.06	Depreciation of active capital
	$\hat{\sigma}$	0.28	Idiosyncratic volatility
Credit	χ	1.06	Debt tax adv. Targets: Leverage $= 0.5$
	θ	0.70	Recovery rate default rate $= 0.02$
	κ_0	0.2	Default-obsolescence feedback
	ϖ	0.5	Default-obsolescence elasticity
Epidemiology	ϑ	0.5	Amount of capital idling to reduce transmission
	γ_I	1/18	Recovery / death rate
	ζ_I	300, 50	Sensitivity of lockdown policy to past infections
	$\tilde{\delta}$	6.5%	Monthly obsolescence of idled capital ($\downarrow$ 10% comm. RE

Effect of the Covid Pandemic

Strategy:

1. Start at 'steady state' of $\hat{g}_{2019}$ (estimated using 1950-2019 data)

2. Run 2 Covid policy scenarios (tough, lite lockdown) $\rightarrow$ 2 COVID shocks ($\tilde{\phi}_{2020}$'s):
   - $\zeta_I = 300 \rightarrow \tilde{\phi}_{2020} = 0.9$, $(\Delta \ln y_{2020} = -10\%)$
   - $\zeta_I = 50 \rightarrow \tilde{\phi}_{2020} = 0.95$, $(\Delta \ln y_{2020} = -6\%)$

3. For each scenario, estimate $\hat{g}_{2020}$

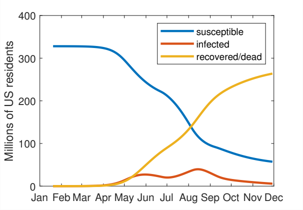
4. Simulate future paths, both with and without future pandemics

5. Compute updated beliefs, aggregate K, Y, N along each path

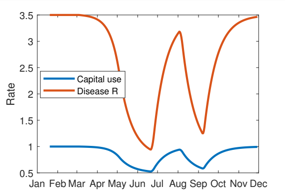
6. Plot the mean future path of aggregates

Scenarios: Infections, Shutdowns and Beliefs

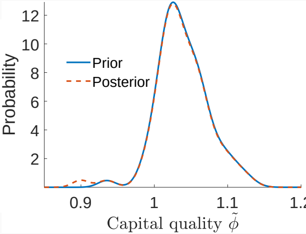
Scenario 1: Aggressive



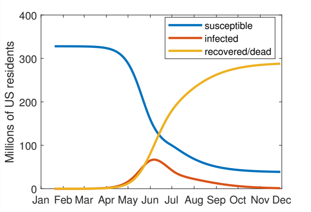
Policy



Beliefs with $\tilde{\phi} = 0.9$



Scenario 2: Lax



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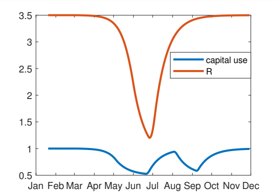
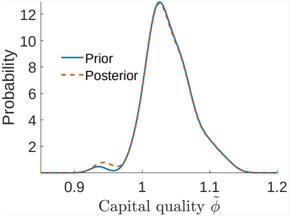
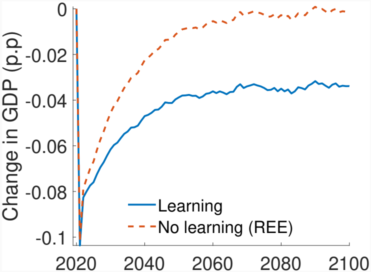


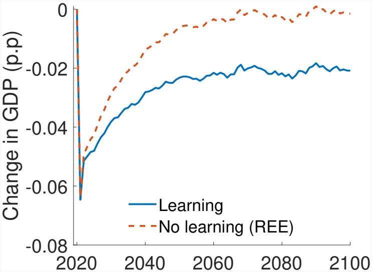
Beliefs with $\tilde{\phi} = 0.95$



Scenario 1



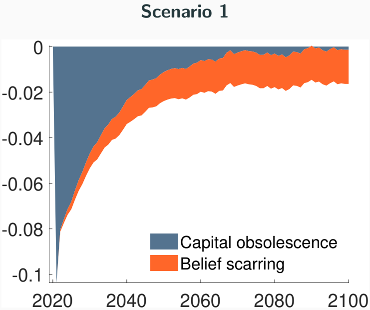
Scenario 2

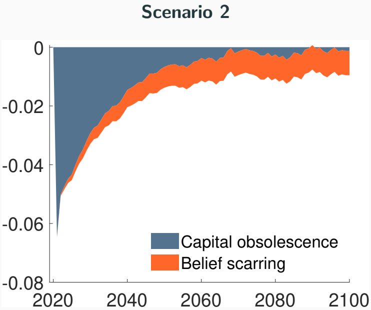


3 reasons costs last beyond 2020 (6%) loss

- Takes time to replenish obsolete capital
- Pandemics continue to occur with positive prob (recur once every 70 years)
- Fear of new pandemics reduces investment (belief scarring)

Where do the losses come from? (if no more pandemics)



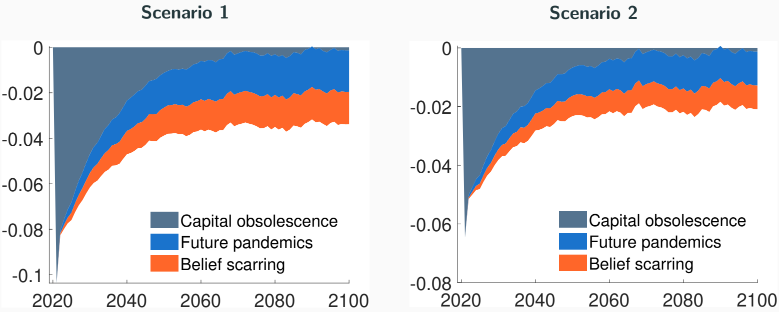


NPV of output losses, in percentages of 2019 GDP

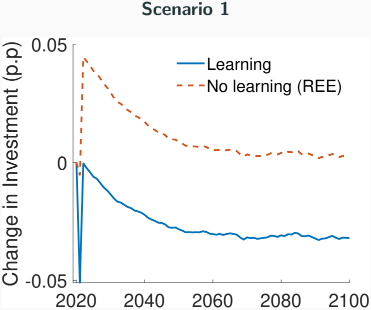
Scenario	2020 GDP drop	NPV(Belief Scarring)	NPV(Obsolete capital)
I. Tough	-10%	-16%	-78%
II. Lite	- 6%	-9%	-48%

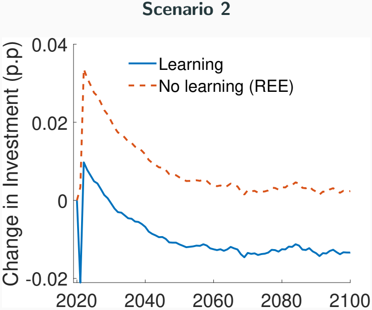
Where do the losses come from? (with future pandemics)

To assess the benefits of public health investments, note that:
Future 1-in-70 year pandemics will subtract another 16% (10%) of GDP in NPV cost. In both cases, this is 1.5 $\times$ the estimated one-year cost of COVID.



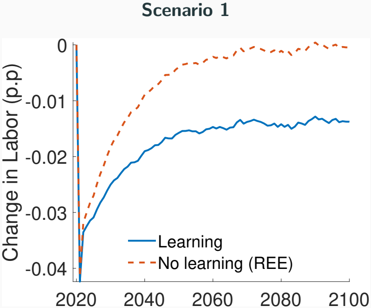
Results: Average Future Investment

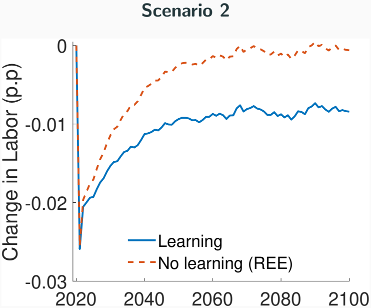




No belief revisions → investment surges

Results: Average Future Labor

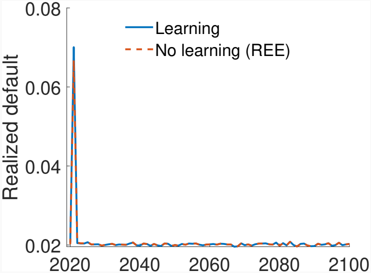




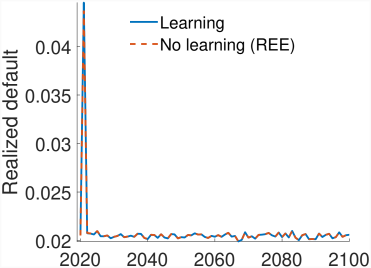
No belief revisions → quick rebound

Results: Average Future Defaults

Scenario 1

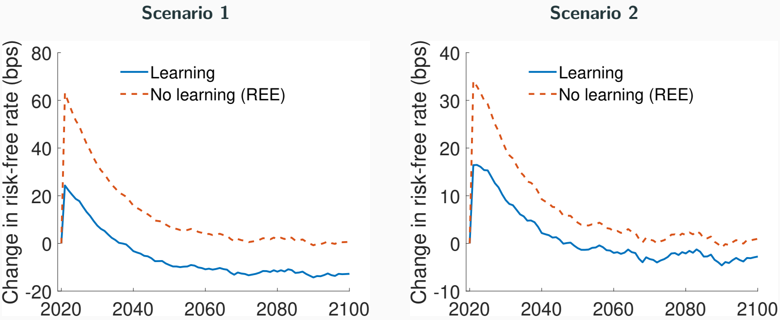


Scenario 2



Realized defaults do not change much (belief revisions $\rightarrow$lower debt).

Results: Average Risk Free Rate



Belief scarring makes safe assets more valuable ($R_f \downarrow$).

Evidence from Asset Markets

Changes in	**Scenario 1**	**Scenario 2**
Asset prices and debt		
Credit Spreads	0.9%	0.1%
Equity Premium	5.2%	1.4%
Equity (Market value)/Assets	0.3%	0.1%
Risk free rate	-0.13%	-0.04%
Debt	-6.3%	-3.6%
SKEW	8.7	1.1
Third moment $E\left[\left(R^e - \bar{R}^e\right)^3\right]$	-1.21	-0.12

Model: Difference between the long run average values under 2009 and 2007 beliefs. For the no-learning model, all changes are zero. Tail risk indicators are under the risk-neutral measure. Data: 2010-2015 average minus 1990-2007 average.

Increase in tail risk produces modest changes in asset markets

What if the learning sample includes Spanish flu?

Potential mechanism

- More data $\rightarrow$ each new observation matters less
- Past tail realizations $\rightarrow$ tail probabilities change less

Two issues

- Historical data on ϕ_t, defaults ?
- Shouldn't we discount old data ?

Strategy: Use the 1950-2020 sample as a proxy for 1880-1949

- Weights: Observation in $t - s$ is given a weight λ^s, $\lambda \leq 1$

Results:

- With no discounting, long run effect cut in 1/2.
- With 1% discounting, Spanish flu almost completely forgotten by 2020. Bigger reaction to more recent data, net effect is the same as baseline.

More data (+ modest discounting) yields similar results

Conclusion

- The effects of COVID and pandemics will not leave us once the vaccine arrives.
  Largest welfare effects are the long-run ones.

- Fact: no one knows the true distribution of shocks.
  Not important for normal events. Matters for tail events.

- New data on rare events permanently reshapes our assessment of macro risks

→ Changes in beliefs substantially amplify cost of tail events.

- Tools for embedding and disciplining belief scarring in quantitative macro models