Understanding Belief Formation — Experience Effects and Information Resonance

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RSF Summer Camp

July 14, 2022

How do Crisis Experiences Affect Beliefs and Decision-Making?

Example: Effect of the COVID-19 Pandemic

1. **Immediate Impact** of being “at home” on behavior/consumption: less or different interaction at work, in stores, with physician etc; online shopping, using yoga/HIIT apps, telemedicine; more trading (Robinhood trending on twitter; GameStop)

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twitter

2. **Medium-Run Impact** of pandemic on earnings and wealth: job loss, job restructuring, educational choices, testing/admissions, vaccination requirements etc.

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3. **Long-Run Impact** of pandemic *beyond* changes (in jobs, health measures etc.) that "are here to stay."
   - How does the experience alter beliefs and behavior in the long-run?
   - How do the long-run effect depend on personal exposure?

A Little Exercise in Magical Thinking

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- Everybody has returned to their pre-pandemic education or job situation; earnings and earnings prospects are as if the pandemic did not happen; impact on accumulated wealth is minimal; all speakers at summer schools are showing up in person ...
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- Basically, we are back to the world of pre-COVID-19.
- **Question:** Under these magical assumptions, would we be back to economic decisions and financial risk-taking from pre-COVID-19?
  - That's what an exclusive focus on SR + MR impact implies.
  - That's not what economists are saying, but arguments build on "economic conditions have changed;" we will not be back to pre-COVID-19 conditions.
  - What about "we have changed" and will behave differently even if the world returned back to its pre-COVID version?

Some Clues from Prior Epidemics

- **Epidemics** such as Bubonic Plagues, Tuberculosis, the 1918 Influenza, or HIV/AIDS generally recognized as essential for historical outcomes during those periods
  - Impact on par with the role of war, religion, economics, and high culture
- For **economic outcomes**
  - Change in demographics (e.g., Black Death transformed the demography of early modern Europe: significant plunge in population growth between the 14th and 18th centuries)
  - Change in GDP
  - Change in trade patterns, trade routes
  - Change in financial capital available
  - ...

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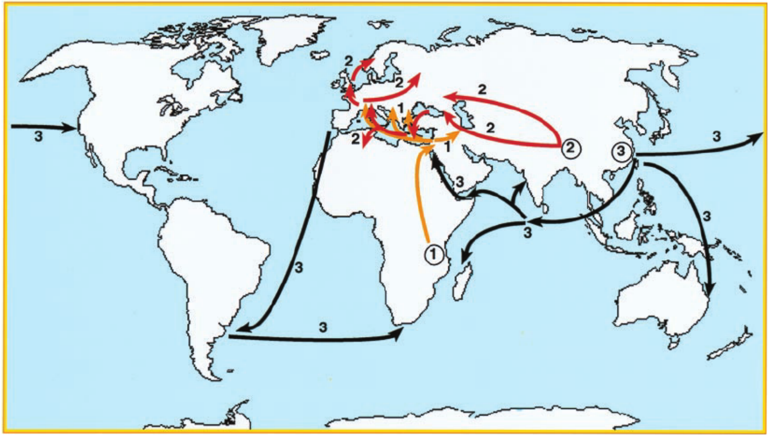
  - ...
  - Change in world views and beliefs

The Three Bubonic Plague Pandemics

(1) Justinian Plague, 5th-7th century
(2) Black Death, 13th-15th century
(3) Modern plague, 1870 onward



The Impact of the Black Death on ‘Belie

- Medical beliefs
  - “In the air” (smoking for health, masks)
  - More attached to certain surfaces than others (leather and waxed fabrics as protection)
- Religious beliefs and World Views
  - Substantially influence on religious beliefs, a new piety, cults of plague saints, and passion plays (Oberammergau).
  - Begin of the modern theodicy discussion
    - “The result was not so much atheism as a mute despair that was most often barely articulated—a psychological shock that, with historical hindsight and anachronism, one might call post-traumatic stress.” [Frank Snowden (Epidemics and Society, 2019)]
  - Emphasis on *vanitas* idea (earthly life is fleeting) ⇒ less investment, including less investment in human capital (education)

Traditional Models of Economic Decision-Making

- Effect of "personally experienced pandemic or crisis" no different from information about outcomes *ceteris paribus*.
- Effect of "living through a depression" on financial investment no different than effect of reading about it; of "having experienced unemployment" on consumption no different than knowing your risk of future unemployment; of living through a pandemic no different from knowing about likelihood and implications (controlling for wealth, income, age, etc.).

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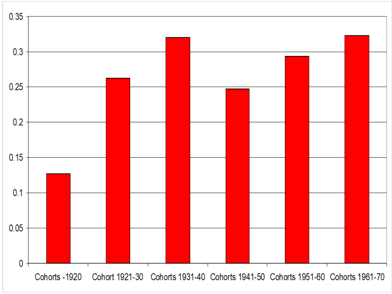
Models and Empirical Evidence of Experience Effects

- Personal experience has lasting impact on beliefs and behavior (scarring effects).
- "Re-wiring" (neuroplasticity, synaptic tagging)

"I don't know about you, but my parents were depression babies, and as a result, avoided the stock market and all things risky like the plague."

Illustration:
stock-market participation rates at age 36-45



- Participation of generation that experienced the 1930s Great Depression as teenagers/adults (13%) significantly lower than that of all other cohorts (26-32%).
- 1931-1940 cohort experienced the post-war boom years during their young adult life, has a participation rate at age 36-45 that is more than twice as high.
- In 1941-50 cohort, the rate dips again, consistent with the fact that this cohort reached age 36-45 just after the depression years of the 1970s.

Approach: Probit model $Pr(y_{i,t} = 1|x_{i,t}, A_{i,t}(\lambda)) = \Phi(\alpha + \beta A(\lambda) + \gamma' x_{i,t})$ in SCF data, with $A_{i,t}(\lambda)$ = weighted sum of past experiences (weights governed by λ) using ML to simultaneously estimate λ and coefficient β.

1. Relate $A_{i,t}(\lambda)$ = investors' "lifetime stock-market experiences" to $y_{i,t}$ = stock investment.
2. Relate $A_{i,t}(\lambda)$ = investors' "lifetime bond-market experiences" to $y_{i,t}$ = bond investment.

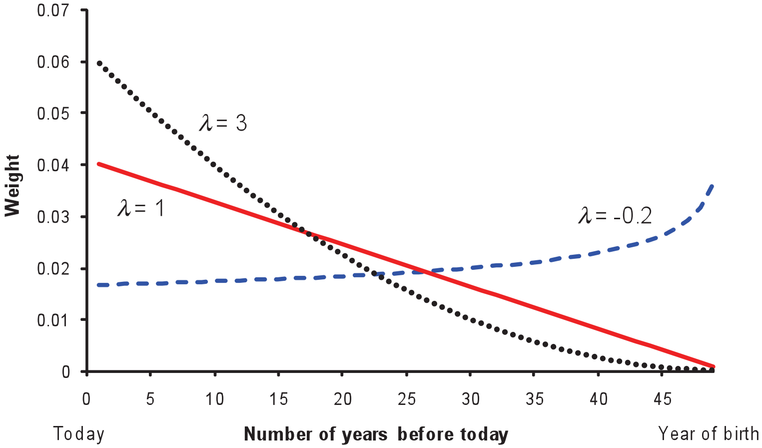
Results

- Stock-market participation (Stock holdings > \$0): IDR +14 pp
- Bond-market participation (Bond holdings > \$0): IDR +15 pp
- No cross-fertilization!

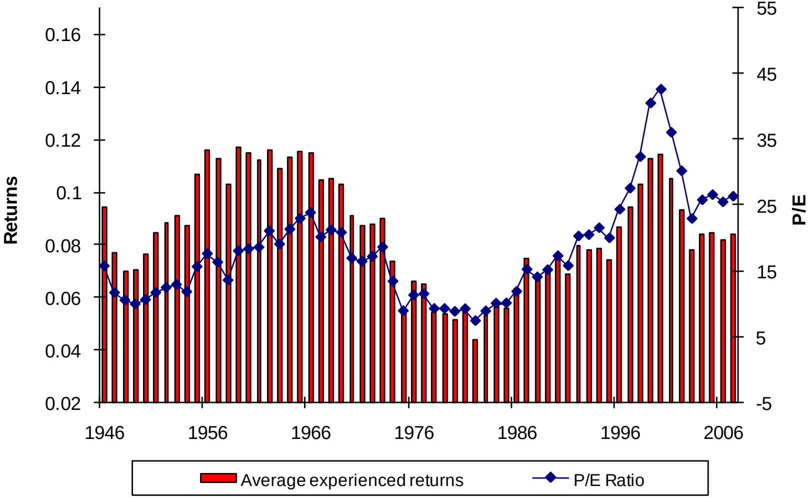
Weighting Function

$$A_{i,t}(\lambda) = \sum_{k=1}^{\text{age}_{i,t}-1} w_{i,t}(k,\lambda) R_{t-k} \text{ and } w_{i,t}(k,\lambda) = \frac{(\text{age}_{i,t}-k)^{\lambda}}{\sum_{k=1}^{\text{age}_{i,t}-1}(\text{age}_{i,t}-k)^{\lambda}}$$

Illustration for 50-year old individual

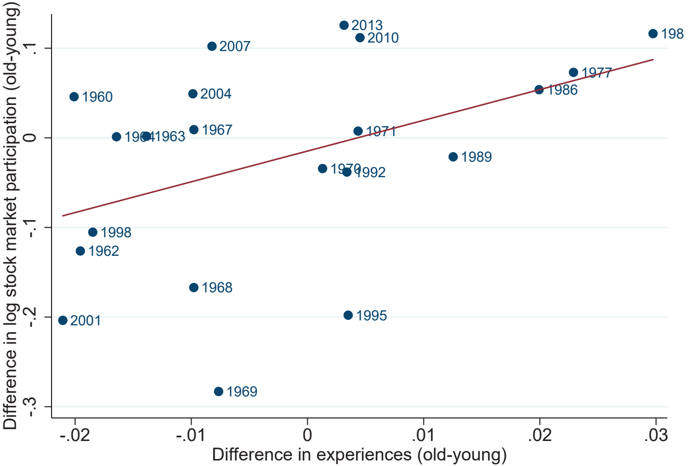


Aggregate Perspective: Market Valuation



Aggregate Perspective (2): Market Composition

$\Longrightarrow$ Speaks to confound "life-cycle stage" / age versus past experiences

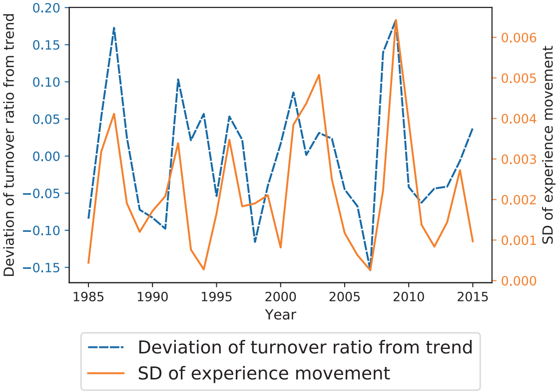


coefficient = 3.432; std.err. = 1.634

Aggregate Perspective (3): Market Dynamics
(Malmendier, Pouzo, Vanasco, JFE 2020)

1. We can integrate experience-based learning in an equilibrium model of asset markets.
   - OLG model of finitely-lived agents with CARA preferences
   - **Heterogeneity (1)**: Belief heterogeneity due to different histories (past experiences)
   - **Heterogeneity (2)**: Younger cohorts react more strongly to a dividend shock than older cohorts as it makes up a larger part of their lifetimes.
   - **Implications for market composition**: A positive shock induces younger cohorts to invest relatively more in risky assets; a negative shock tilts the composition towards older cohorts.
   - **Implications for trade volume**: Changes in the level of disagreement between cohorts lead to higher trade volume in equilibrium.
2. We can test these implications empirically.

Trade Volume



Trading volume = market-cap weighted average monthly TO ratio (shares traded over shares outstanding)
Deviation of TO ratio: log, linearly detrend, and CF-filter the yearly variable

Returns = inflation-adjusted increase in price over prior year; linearly detrended and CF-filtered
SD = current-year population-weighted SD of the changes in experienced returns across age-cohorts

Aggregate Perspective (4): International Capital Flows (Malmendier, Pouzo, Vanasco, JIE 2020)

Experience effects help explain classic international macro puzzles regarding capital flows and portfolio investment, namely the tendency of investors to

1. hold an over-proportional fraction of their equity wealth in domestic stocks (home bias)
2. invest in domestic equity markets in periods of domestic crises (retrenchment),
3. withdraw capital from foreign equity markets in foreign & global crises (fickleness).

Basic intuition: More exposure to domestic risky-asset returns $\Longrightarrow$ more precise prior.

Aggregate Perspective (4): International Capital Flows (Malmendier, Pouzo, Vanasco, JIE 2020)

Experience-based learning generates additional implications regarding

- the strength of these puzzles depending on the demographic composition.
- the strength of these puzzles in times of higher or lower economic activity,
- Intuition:
  - Countries with a larger number of young market participants overreact (more) to both domestic and foreign shocks.
  - As a result, retrenchment and fickleness are alleviated in young-demographics countries.
  - Cf. Heterogeneity (1) and (2) results above, applied internationally.

All tested and confirmed in data from the IMF, World Bank, World Federation of Exchanges.

Identifying Variation

Sources of variation in experience effects:

1. Cohort (exposure to macro-level realizations)
   - Generates generational effects (Gen X, Gen Y, Millenials ... Who will be Gen COVID? Along what dimension will they be scarred?)
   - Generates differences in generational differences over time, with generations diverging and converging depending on how their average lifetime experiences compare.
2. Location (exposure to local realizations)
3. Individual (individual experiences)

Identifying Variation

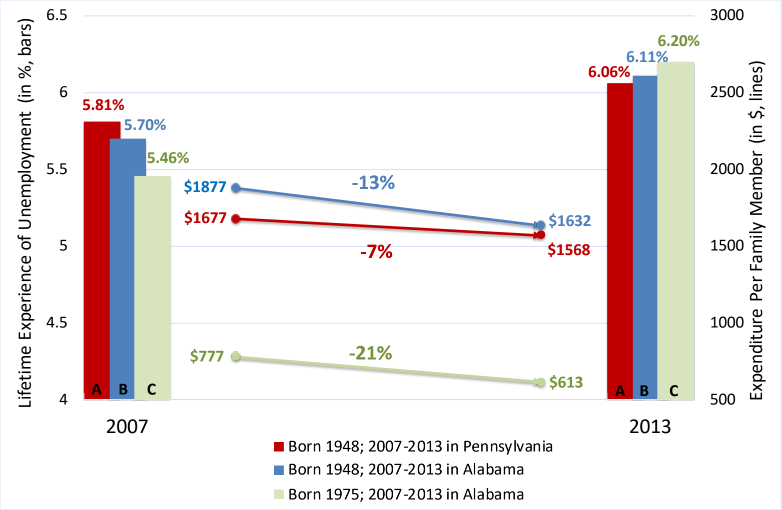
Example: "Scarred Consumption" (Malmendier and Shen, 2020)

$$C_{it} = \alpha + \psi UEP_{it} + \beta UE_{it} + \gamma' x_{it} + \eta_t + \varsigma_s + \upsilon_i + \varepsilon_{it}$$

with

- C_{it} = total consumption;
- UEP_{it} and UE_{it} = i's past personal and macro (local/national) unemployment experience;
- x_{it} = vector of controls for wealth (liquid, illiquid), income, lagged income, age, employment, family size, gender, education, marital status, race;
- Indicators η_t for time (year), ς_s for state, υ_i for household.

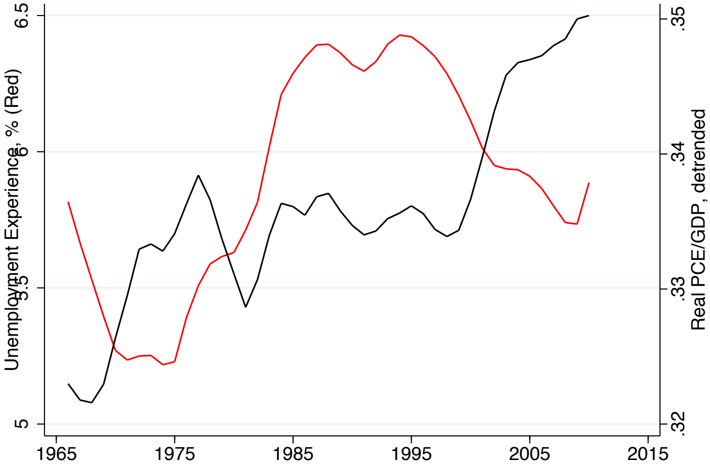
Illustration: Location-Based Variation in Con. Scarring



Findings

Experience of personal and macro (local/national) UE years (decades) in the past

1. predicts lower consumption spending (PSID, Nielsen, CEX)
2. predicts pessimistic beliefs about own and economy-wide financial conditions (MSC)
3. does not predict lower or more volatile future income (PSID)
4. predicts higher wealth-build up (savings) (PSID)



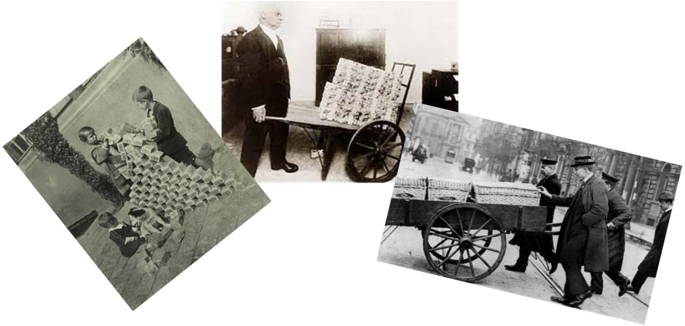
Unemployment Experience, % (Red)
Real PCE/GDP, detrended
6.5
6
5.5
5
.35
.34
.33
.32
1965
1975
1985
1995
2005
2015

Experience Effects – Key Features

1. Experiences over one's lifetime so far have long-lasting effects on beliefs and choices.
   - Different cohorts are affected differently.
2. Experiences are domain-specific.
   - No cross-fertilization between different realms of economic decisions.
   - Same pattern across domains (stocks, bonds, inflation, interest rate expectations, unemployment experiences etc.)
3. Extent of exposure matters.
   - Different locations are affected differently.
   - **Implication**: Different genders/races/... are affected differently in the long-run, even exposure has passed.
   - **Implication**: Interaction with inequality.
4. Robustness (imperviousness) to **learned knowledge**: Experiences affect experts.

Example: Inflation Experiences $\Longrightarrow$ Inflation Beliefs

German motivation ...



... and US motivation

Paul Volcker (1979):

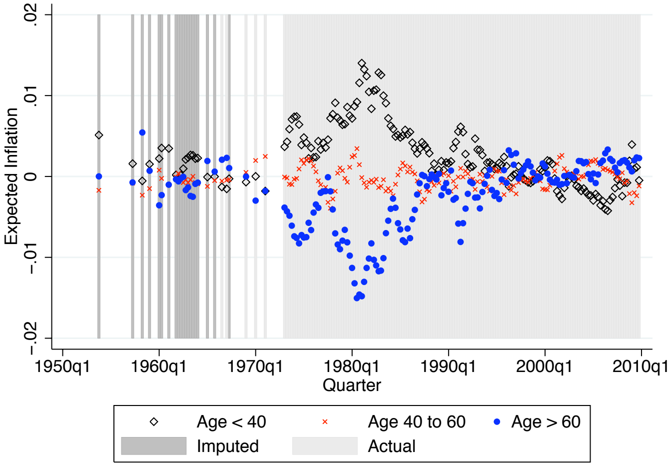
"An entire generation of young adults has grown up since the mid-1960s knowing only inflation, indeed an inflation that has seemed to accelerate inexorably. In the circumstances, it is hardly surprising that many citizens have begun to wonder whether it is realistic to anticipate a return to general price stability."

Findings: Inflation Experiences ⟹ Inflation Beliefs

Malmendier and Nagel (2016), using MSC data since 1953

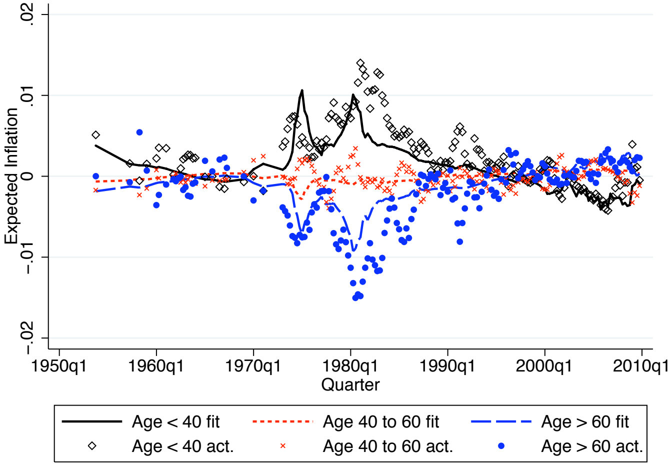
1. When forming inflation expectations, individuals put a higher weight on realizations experienced over their life-times than on other available historical data.
   - Similar to adaptive learning: people learn following simple "rules of thumb" (e.g., Bray 1982; Marcet and Sargent 1989)
   - Different from adaptive learning: people learn (more) from data realized during their lifetimes. (adaptive learning: all historical data)
2. Implicit weighting of past experiences very similar to weighting pattern in other applications, e. g., stock market!
   - Roughly linearly declining weights.
3. Significant impact on individual financial decisions, namely, long-term nominal-rate borrowing and lending (tenure, ARM/FRM, refi, bonds).

Disagreement about future inflation (MSC)



Four-quarter moving averages of one-year inflation expectations shown as deviations from the cross-sectional mean.

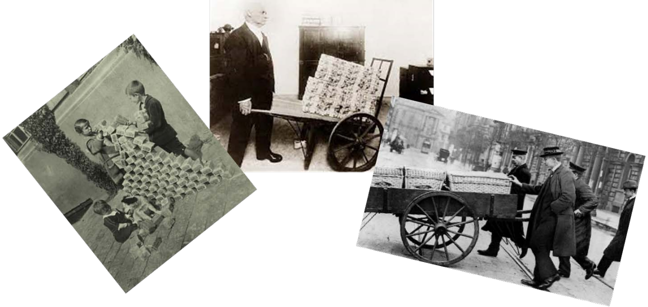
Fitted expectations



Fitted and actual relative to full-sample c.s. mean (4-quarter MA)

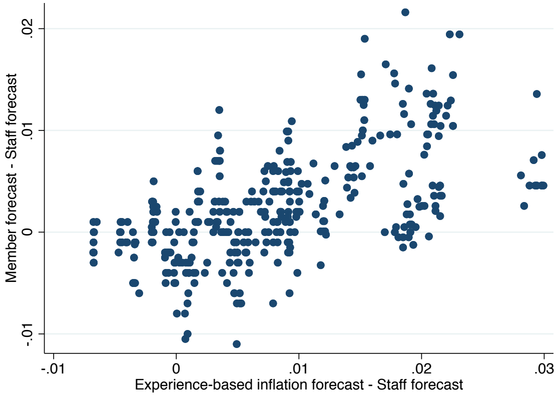
Inflation Experiences of Experts

Malmendier, Nagel, and Yan (2020)



- Henry (Heinrich) Wallich: Fed governor 1974-1986
    - Born in Germany in 1914 into a family of bankers.
    - Lived through Germany's hyperinflation in 1923.
    - Emigrated to the US in the 1930s.
- Wallich dissented 27 times (!) during his tenure on the Fed Board, the highest number of dissents in Federal Reserve history, decades later.

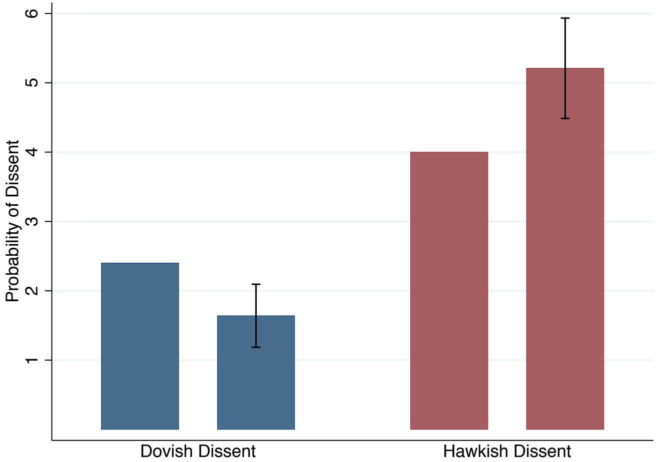
FOMC Members' Inflation Experiences and Forecasts



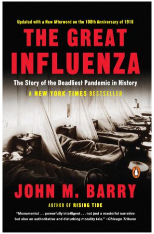
Member forecast: from semi-annual Monetary Policy Report to Congress, 1992 - 2004.
Staff forecast: Greenbook forecast.
Experience-based forecast: AR(1) model forecast estimated based on weighted life-time inflation data for each FOMC member.

Inflation experiences and FOMC voting behavior

Effect on dissent probabilities of $+0.1$pp rise in experience-based inflation forecast



Experience Effects (even) in Experts



- Finance: evidence from fund managers, bankers, doctors
- Pandemic: John Barry (infectious disease researcher)
  - Q: "Did you expect, when you wrote the book, that you would witness a pandemic like the one we are enduring now?"
  - A: "I think anybody who understands anything about infectious disease recognized that we were going to, sooner or later, face something like this. ... But, intellectually understanding it, is one thing, and having it hit you is something quite different. So, I am like everyone else in that sense."

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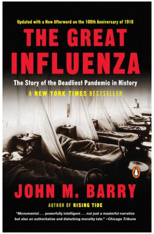

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- A bit of etymology: *experiri*, *experiens*
  - *ire* $\Longrightarrow$ *per* $\Longrightarrow$ *ex*
  - *experiri, experior, expertus sum*

INFORMATION VS. REWIRING

- Traditional economic explanation for effects of past exposure on beliefs: information
- Results (taken together) challenge information channel, esp. applicability to experts (FOMC member, fund managers, bankers, physicians)
- Results challenge some behavioral channels, e. g., limited attention, cognitive challenges.

Information $\longrightarrow$ Software $\longrightarrow$ Hardware

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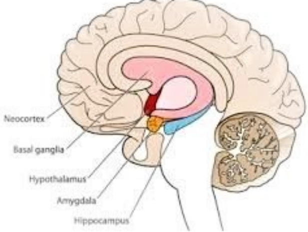
NEUROPLASTICITY
(CF. LAUDENBACH, NIESSEN-RUENZI, MALMENDIER AEA P&P 2019; NBER WP 2020)

- Every time we have a new experience, our brain forms a connection between two neurons (synapse).
  - Synapses tell our body how to react to the world around us. The govern the way we experience life.
- The brain can reorganize pathways, create new connections, and even create new neurons (neuroplasticity) in response to learning, experience, and memory foundation
- Generally, young brains tend to be more sensitive and responsive to experiences than older brains. But the brain never stops changing.

Synaptic Tagging



- How and how often we make an experience matters.
  - Repeated stimulation of hippocampal neurons can induce a prolonged increase in synaptic strength (long-term potentiation (LTP)), Cf. Frey and Morris (*Nature* 1997, *Trends in Neuroscience* 1998))
  - Emotional Tagging: **Emotional events attain privileged status in memory**, Dolan *Science* (2002), LaBar and Cabeza *Nature* (2006).
  - Prior or subsequent "learned knowledge" has very limited power to undo the effects.

- Cf. literature on trauma: Synaptic changes caused by traumatic stress (Mahan and Ressler *Trends in Neuroscience* 1998, Zhang et al, *Front Psychol* 2020).

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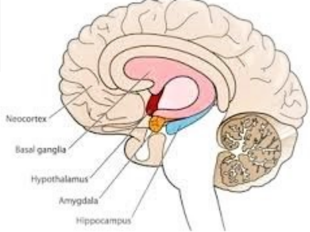

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- Cf. literature on trauma: Synaptic changes caused by traumatic stress (Mahan and Ressler *Trends in Neuroscience* 1998, Zhang et al, *Front Psychol* 2020).
  - Trauma with a big T: German Hyperinflation, Great Depression, Pandemics
  - trauma with a small t: Daily Exposure, daily worry about food, prices, unemployment
  - Other repeated (non-traumatic) exposure, including positive experiences

Example: Gendered Experiences

D'Acunto, Malmendier, Weber (PNAS, 2020)

Within-Household Inflation Expectations

- Women have (more) positively biased inflation expectations, even within households.
- Unconditional difference driven by differences in grocery shopping.

Evidence on Experience Effects – Applications

Evidence of personal experiences affecting beliefs and choices from finance, macro, labor, international economics, real estate, ... (Cf. QJE, JPE, JF, JFE, AEJ Macro, JME, JIE)

- IPO investment
- stock-market investment (Depression Babies, East Germany)
- bond-market investment
- tenure decisions (buy versus rent)
- mortgage choices
- consumption spending (and unemployment experiences)
- grocery shopping

(Kaustia and Knuepfer 2008; Malmendier and Nagel 2011, 2016; Botsch and Malmendier 2021; Mamendier and Steiny 2020; Malmendier and Shen 2020; Laudenbach et al. 2021; D'Acunto et al. 2021)

Approaches to Expectation Formation

1. **Traditional**: Bayesian updating, perfect cognition, perfect information processing
   - Frictions: access to information, model uncertainty
   - Remedy: improve access to information (hence, info experiments), reduce model uncertainty

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3. **Biological** [neuro, cognition]: Humans' views of the world and beliefs are altered by their personal experiences, by events that resonate $\Longrightarrow$ dynamically changing process (brain plasticity, trauma, scars), independent of information and processing abilities
   - Frictions: information processing function of prior exposure
   - Remedy: design of experiences

Example 1: COVID-19 Vaccination

What explains differences in views about COVID-19 vaccination?

1. **Traditional**: Different beliefs due to differences in information
2. **Behavioral**: "Breakthrough cases prove vaccines are useless"
   - 0.05% of vaccinated people have been hospitalized or died from COVID-19.
   - 99.5% of COVID-19 deaths are unvaccinated people
3. **Experience effects**: Humans change their views about vaccines after personally being infected and witnessing cum/ex vaccine differences
   - Pre-vaccine/attitudes towards C19 measures: Justin Trudeau's wife, Boris Johnson
   - Closing of the Black-White vaccination gap by employing local community members, videos with Tuskegee descendants

Example 2: Inflation Expectations

What explains the overweighting of food and gas prices?

1. **Traditional**: Different beliefs due to differences in information
2. **Behavioral**: Biases / limited cognition
3. **Experience effects**: Humans change their views of future inflation, as well as savings/spending decisions, after personally being affected
    - Even if fully informed about inflation data

Approaches to Expectation Formation

1. **Traditional**: Bayesian updating, perfect cognition, perfect information processing
   - Frictions: access to information, model uncertainty
   - Remedy: improve access to information (hence, info experiments), reduce model uncertainty

2. **Behavioral**: Flaw in the software (biases), e.g., over-inference (overweighting recent information), natural expectations (not enough lags), overconfidence etc.
   - Frictions: info processing flaw, imperfect cognition
   - Remedy: Education (interest rate compounding, Bayes' Rule)

3. **Experience effects**: Humans' views of the world and beliefs are altered by their personal experiences, by events that resonate $\Longrightarrow$ dynamically changing process (brain plasticity, trauma, scars), independent of information and processing abilities
   - Frictions: information processing function of prior exposure
   - Remedy: design of experiences

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Generalization beyond *Personal* Experiences

- What information will be anchored in our brains? What will be "tagged"?
  - Direct personal experiences
  - Indirect experiences: people close to me, people similar to me?
- Some existing evidence from macro, finance, and labor
  - Inflation: D'Acunto, Fuster, Weber (2021): Gender and race (for Black men), gender (for white/Black women) in updating inflation expectations
  - Finance: Stolper and Walter (2018): Gender and age (for men), marital and parental status (for women) in updating financial beliefs/taking financial advice
  - Health: Alsan et al. (2019): Gender and race (for Black men) for health beliefs / taking health advice – though personal interaction more than pictures
  - Education: Large literature on role models in labor economics (STEM TAs, math professors): gender, race, especially older students (8th grade+)

Information Resonance
(Malmendier and Veldkamp 2022)

- Despite hearing information, people might ignore/do not act upon it if it does not "resonate" with them; and they do if it does resonate.
  - How powerfully information affects decisions depends on how firmly that information is anchored in memory/thinking.
    Emotionally identifying with an experience anchors it.
- Similar characteristics θ elicit resonance. ("That could have been me!")
  - Race, religion, politics, profession, gender, sexual orientation, . . . of actor and observer matter. (Social learning theory)
  - But not uniform $||\theta_{f,race1} - \theta_{f,race2}|| \neq ||\theta_{m,race1} - \theta_{m,race2}||$
  - Cf. intersectionality debate (understood as 'interaction effects')

Goals

1. Formalize information resonance:
   Information diffusion along a socio-economic space.
   $\Longrightarrow$ Tool to identify the relevant dimensions (What resonates?)

2. Implications: three ways in which information resonance differs from information access
   - Decline of Expertise (1): The experience of a community leader is a powerful signal.
     Celebrities and experts are less effective.
     (Fauci vs. local priest; Jerome Powell vs colleague at work)
   - Decline of Expertise (2): Information access and resonance interact.
     Broader access to information reduces reliance on experts, especially for social outliers.
     (Endogenous network formation.)
   - Crises can shift community norms.

3. Develop empirical tool based on simply ML approaches.
   For now: suggestive empirical evidence from occupational choices.

Formalization

1. Agents are uncertain about payoff from choosing an action $a \in \{0, 1\}$. The payoff for agent i is z_i if $a = 1$
$$U_i(a_{it}) = a_{it} \cdot z_i + \epsilon_{it} \tag{1}$$
where $\epsilon_{it} \sim iid\ N(0, \sigma_\epsilon^2)$
2. The vector of payoffs for all agents has correlated entries: $z \sim N(\mu_z, \Sigma_z)$
3. Agents learn from observing own and other agents' experiences (action-payoff pairs) if uncertain-payoff action is taken: $(a_{jt}, 1_{a_{jt}=1}(z_j + \epsilon_{jt}))$
4. Standard Bayesian updating, except resonance (ω_{ij}) tilts weights. For an agent i taking action $a_{it} = 1$:
$$E[z_i | \mathcal{I}_{it}] = \alpha_i \mu_z + \overline{\omega}_i \sum_{j=1}^{N} \sum_{t'=1}^{t} \omega_{ij} \beta_{ij} (z_j + \epsilon_{jt'}), \tag{2}$$
where α_i and β_{ij} are i's Bayesian weights on priors and signals from agent j and $\overline{\omega}_i$ allows ω to be scale-neutral.

Formalization (2)

- β_i is the standard OLS estimator that projects individual payoff onto signal space: $\beta_i = Var(z+\epsilon)^{-1} Cov(z_i, z+\epsilon)$. $\alpha_i = 1 - \sum_{j=1}^{N} \beta_{ij}$.
- Resonance down-weights observation of others with dissimilar characteristics θ:

$$\omega_{ij} = 2 \cdot (1 - \Phi(\chi \underbrace{||\theta_i, \theta_j||}_{dissimilarity}))$$

  where Φ is a normal cdf, $||\cdot||$ is Euclidean distance.
  χ indexes importance of resonance.

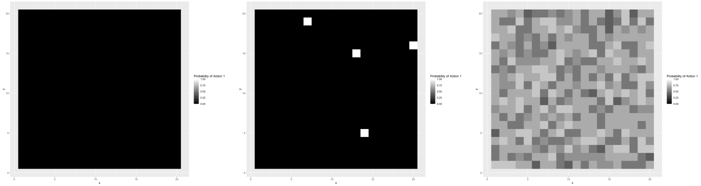
- Timing and Equilibrium:
  1. Agents, indexed by type / characteristic θ_i, have prior beliefs, μ_{it}, Σ_{it}.
  2. Each agent chooses a single action $a_{it} = 1$ or 0.
  3. All payoffs realized and observed by all agents.
     Update beliefs with (2). Repeat.

Model Discussion

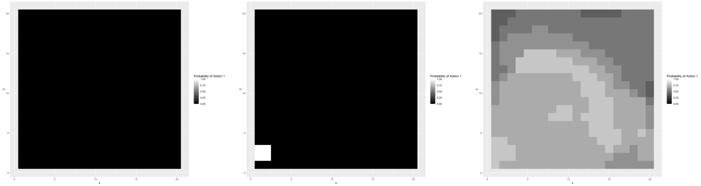
- Characteristics: What are θ's?
- What cognitive mechanism does this represent?
  - Memory, anchoring, synaptic tagging:
    I remember information that resonates
  - Perceived precision:
    I believe information that resonates or think it is more relevant for my circumstance.
  - Bayesian beliefs, with action distortion:
    Resonant information sways my actions, but not my beliefs.
    ("I know that x is true, but still ...")

Illustration: Geographic and Characteristic Space

Geographic space at $t = 0, 5, 10$:



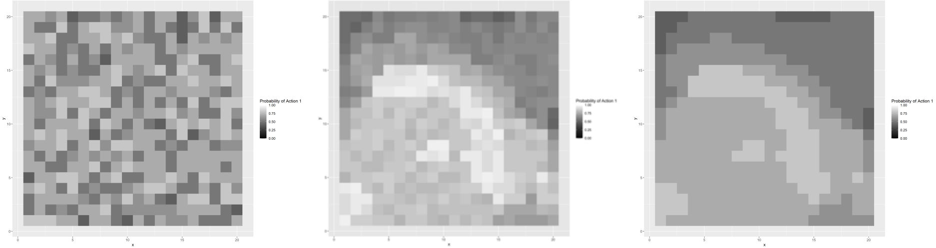
Same result in characteristic space at $t = 0, 5, 10$:



- Geographic outcomes look like random shocks, not diffusion.
- Characteristic space makes the diffusion visible.

What is the Right Characteristic Space?

Sorting on completely wrong, partially wrong and correct characteristics: at $t = 5, 10$:



- If we want to see a neat diffusion and make clear predictions, it is important to know which characteristics to sort on.
- How can we measure the resonance-relevant characteristics?

Measuring Resonance

- Suppose we see actions and characteristics.
  We know that the true covariance of payoffs is Σ_z.
- **Lemma**: There exists a covariance of payoffs Σ^R that rationalizes the actions of agents, with Bayesian beliefs.
- We can use this to estimate resonance.
  - With survey data: Regress the forecast on neighboring outcomes $(z + \epsilon)$

    $$E[z_i|\mathcal{I}_{it}] = \alpha + \beta_i^R(z+\epsilon) + \eta_{it}$$

  - For binary actions: Estimate coefficients of a logit

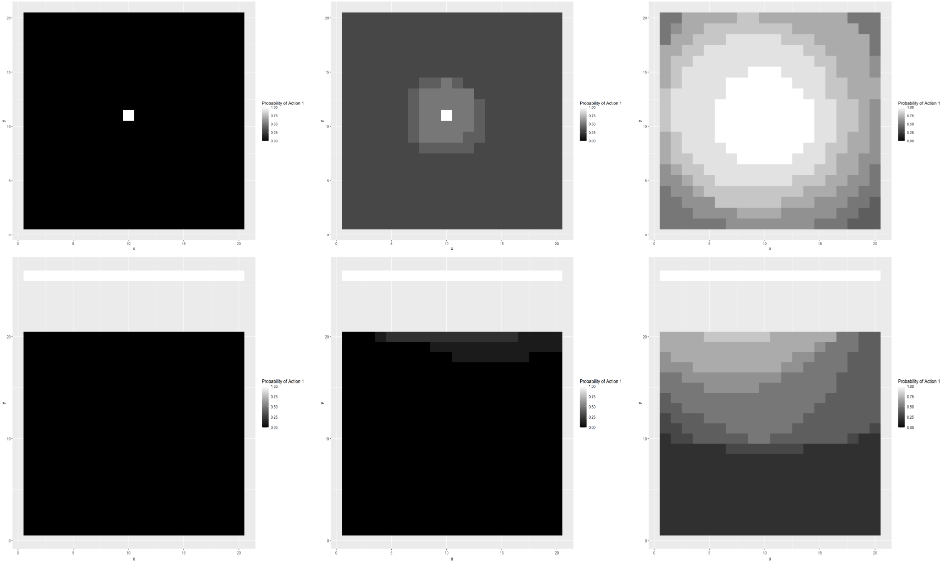
    $$Pr[a_i = 1|\mathcal{I}_{it}] = \Phi\left(\alpha + \beta_i^R(z+\epsilon) + \eta_{it}\right)$$

  - Then map the sensitivity estimate β_i^R into a (scaled) resonance weight:

    $$w_i\bar{w}_i = \beta_i^R./\beta_i = (I + \sigma_\epsilon^2\Sigma_z^{-1})\beta_i^R$$

    This requires knowing (1) the true payoff covariance Σ_z, (2) the true model of choice, and (3) observability / information frictions.

Prediction 1: Local leaders inspire change



Prediction 1: Local leaders inspire change

- Characteristics are evenly spaced on an $n \times n$ grid.
- At date $t = 1$, either
  1. A local leader, located in characteristic space at $(int n/2, int n/2)$ takes action 1, where $int\cdot$ represents rounding to the nearest integer; or
  2. $\tilde{J}$ adjacent neighbors, each $\gamma > 1$ spaces away from the nearest community member, in characteristic space, all take action 1.

Proposition

In order to have an equal probability of getting the nearest community member to switch to choosing $a = 1$ at date $t = 2$, as one local leader in scenario 1, it requires $\tilde{J}$ neighbors in scenario 2, where $\tilde{J}$ solves

$$Q_1 \tilde{J} + Q_2 \tilde{J}^{1/2} + Q_3 = 0,$$

with $Q_1 = \omega_n(E[z_0|\mathcal{I}_0] - z_1)$, $Q_3 = \sigma_1^{-2}(E[z_0|\mathcal{I}_0] - \mu_1)$, and $Q_2 = (\omega_n/\omega_{ll})Q_3 - Q_1$.

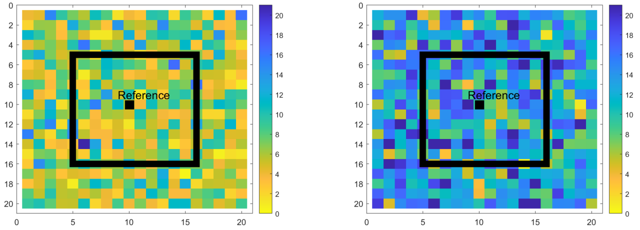
ω_{ll} is weight closest nodes put on the local leader's experience.

ω_n is weight closest neighbors put on the experience of neighbor community.

Prediction 2: The Decline of Expertise

- Proposition: Celebrity/ expert actions have more influence on others' beliefs when agents are geography-constrained ($\partial E[z_a|\mathcal{I}]/\partial a_{celeb}$ larger)

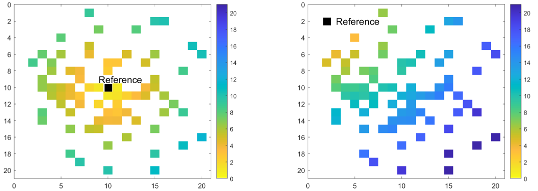
An centrist agent (left) and one with extreme characteristics (right)
(a) in geographic space:



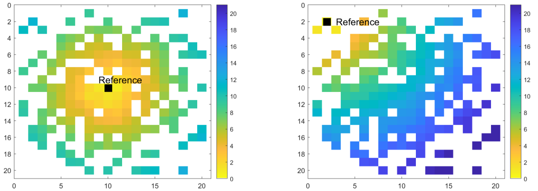
- Warmer colors represent social proximity.
- Agent on the right has few warm dots = few neighbors whose experiences resonate.
- Without social networks, people see physical neighbors (inside black box). With social network, everyone is visible.

Prediction 2: The Decline of Expertise

(b) in characteristic space, with geographic information constraints (in box):



(c) in characteristic space, with no information constraint:



Extreme agent (right) gets more resonant information with social network.

More resonant information (bottom right panel) is what reduces weight on outside experts.

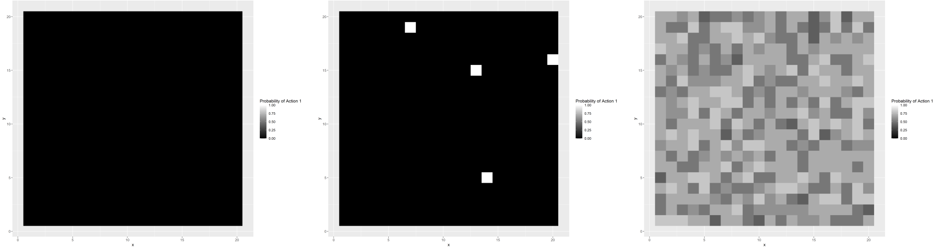
Prediction 3: Crisis as a Time of Re-invention

Proposition: When no agents in a community choose action 1 and both actions suffer a negative payoff shock, an agent in that community is more likely to choose 1 next period.

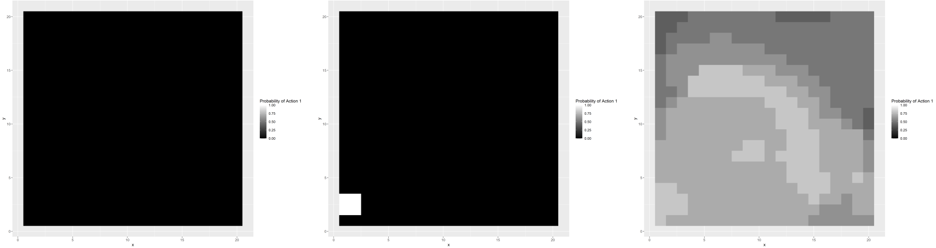
- Both payoffs get worse. But you only observe the payoff in your community from action 0 fall. You do not know the other payoff also fell. Agents switch actions.
- The grass looks greener on the other side.

Prediction 3: Crisis as a Time of Re-invention

Geographic space at $t = 0, 5, 10$:



Same result in characteristic space at $t = 0, 5, 10$:



Empirical Analysis motivated by Crisis Application

- Model Hypotheses
  1. Hypothesis 1: Information about job choices among socially close community members resonates more.
  2. Hypothesis 2: Layoffs of socially close community members resonate more than layoffs in industries where community members are underrepresented.
- **Empirical Predictions**

  Prediction 1: Young (age 18-22) of ethnicity i in region k are more likely to choose occupation j in year t if adult (age 26-65) members of (ethnicity i) are overrepresented in occupation j, region k at time t.

  Prediction 2: If occupation j experienced high layoffs in region k during the Great Recession, then young members of ethnicities overrepresented in occupation j are deterred from entering the occupation j in region k post-crisis.

  Prediction 3: Effects are stronger when matching multiple demographic characteristics– young members of an ethnic community will enter occupations in which elders of the same ethnicity and gender are overrepresented.

Data and Variable Construction

- Microdata from the annual American Community Survey (ACS) from 2005 to 2020, obtained via IPUMS, which includes variables describing age, occupation, migration and ancestry.
- Using IPUMS variables detailing occupation and ancestry, we categorized each individual into one of 32 occupation groups based on the 1990 Census codes and 17 ethnic groups based on global geographic regions.
- In order to identify local communities, we use 1,078 Public Use Microdata Areas (PUMA), the smallest geographic identifier available in the ACS. The combination of an individual's ethnicity and PUMA becomes our measure of social proximity.
- We separate the data into two age cohorts: (1) People aged 26-65 to get baseline measures for the fraction of people in an (ethnicity i) $\times$ (occupation j) $\times$ (PUMA k) $\times$ (year t). (2) People aged 18-22 who have recently chosen their occupation.

- **Variable Construction**
  1. Fraction measures the fraction people aged 26-65 of ethnicity i in occupation j in PUMA k during year t.

$$Fraction_{i,j,k,t} = \frac{Freq_{i,j,k,t}}{Total_{i,k,t}}$$

  2. Total Fraction measures the fraction of people ages 26-65 in occupation j in PUMA k during year t.

$$Total\ Fraction_{j,k,t} = \frac{Freq_{j,k,t}}{Total_{k,t}}$$

  3. Difference measures ethnic over-representation in an occupation in their PUMA.

$$Difference_{i,j,k,t} = Fraction_{i,j,k,t} - Total\ Fraction_{j,k,t}$$

  4. Youth Rate is the fraction of people aged 18-22 of ethnicity i in occupation j in PUMA k during year t.

$$Youth\ Rate_{i,j,k,t} = \frac{Freq_{i,j,k,t}}{Total_{i,k,t}}$$

Results: Prediction 1

Table: Occupation Choice: Ethnicity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Difference	0.0766***	0.125***	0.124***	0.133***	0.121***	0.131***	0.0424***
	(0.0203)	(0.0103)	(0.0103)	(0.0112)	(0.00956)	(0.0109)	(0.0129)
Constant	0.0313***	0.0212***	0.0313***	0.0313***	0.0313***	0.0313***	0.0313***
	(0.000244)	(0.000531)	(0.000107)	(0.000101)	(0.0000781)	(0.0000990)	(6.29e-15)
Occupation FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	No	Yes	No
Ethnicity FE	No	No	No	Yes	No	No	Yes
PUMA FE	No	No	No	No	Yes	Yes	Yes
Occupation*Year FE	No	No	Yes	No	No	No	No
Occupation*Ethnicity FE	No	No	No	Yes	No	No	No
Occupation*PUMA FE	No	No	No	No	Yes	No	No
Occupation*PUMA*Year FE	No	No	No	No	No	Yes	No
Occupation*PUMA*Ethnicity FE	No	No	No	No	No	No	Yes
Observations	1148672	1148672	1148672	1148672	1148352	1005312	1142080

Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results: Prediction 1

Table: Occupation: Ethnicity, Gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Difference	0.474***	0.429***	0.429***	0.442***	0.432***	0.441***	0.393***	0.773***
	(0.0107)	(0.00572)	(0.00573)	(0.00606)	(0.00540)	(0.00594)	(0.00668)	(0.00686)
Difference (Wrong Gender)	-0.242***	-0.326***	-0.326***	-0.311***	-0.321***	-0.319***	-0.361***	0
	(0.0108)	(0.00557)	(0.00557)	(0.00582)	(0.00526)	(0.00584)	(0.00647)	(.)
Constant	0.0312***	0.0208***	0.0312***	0.0312***	0.0312***	0.0312***	0.0312***	0.0312***
	(0.000252)	(0.000453)	(0.0000952)	(0.0000897)	(0.0000677)	(0.0000732)	(3.78e-19)	(2.90e-19)
Occupation FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	No	Yes	No	Yes
Ethnicity FE	No	No	No	Yes	No	No	Yes	Yes
PUMA FE	No	No	No	No	Yes	Yes	Yes	Yes
Occupation*Year FE	No	No	Yes	No	No	No	No	No
Occupation*Ethnicity FE	No	No	No	Yes	No	No	No	No
Occupation*PUMA FE	No	No	No	No	Yes	No	No	No
Occupation*PUMA*Year FE	No	No	No	No	No	Yes	No	No
Occupation*PUMA*Ethnicity FE	No	No	No	No	No	No	Yes	No
Occupation*PUMA*Ethnicity*Year FE	No	Yes	No	No	No	No	No	Yes
N	2108064	2108064	2108064	2108064	2107904	2056448	2104672	1809472

Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

RESULTS: PREDICTION 2

TABLE: Impact of a Shock on Occupation Choice (2005/06 and 2010/11)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Difference_{2005}	0.0351	0.0619*	0.0424	0.162***	0.0339	0.0413	0
	(0.0506)	(0.0354)	(0.0354)	(0.0390)	(0.0356)	(0.0387)	(.)
POST=1	0.000768	0.000755	0	0.000725	0.000706	0	0.000719
	(0.000479)	(0.000472)	(.)	(0.000472)	(0.000495)	(.)	(0.000472)
(POST)*(Difference_{2005})	0.0733	0.0342	0.0698	0.0341	0.0237	0.0316	0.0268
	(0.0519)	(0.0503)	(0.0502)	(0.0501)	(0.0522)	(0.0555)	(0.0503)
High Layoffs	-0.0174***	0.00157***	0.000105	0.00139***	0	0	0
	(0.000681)	(0.000525)	(0.000522)	(0.000522)	(.)	(.)	(.)
(High Layoffs) *(Difference_{2005})	0.156*	0.209***	0.230***	0.145*	0.299***	0.296***	0
	(0.0939)	(0.0750)	(0.0746)	(0.0752)	(0.0754)	(0.0804)	(.)
(POST)*(High Layoffs)	-0.00267***	-0.00249***	0.000466	-0.00239***	-0.00235***	0	-0.00240***
	(0.000760)	(0.000752)	(0.000747)	(0.000752)	(0.000790)	(.)	(0.000757)
(POST)*(High Layoffs)*(Difference_{2005})	-0.272***	-0.270***	-0.309***	-0.275***	-0.273**	-0.296***	-0.289***
	(0.105)	(0.104)	(0.103)	(0.104)	(0.109)	(0.115)	(0.105)
Constant	0.0384***	0.0192***	0.0331***	0.0327***	0.0332***	0.0328***	0.0331***
	(0.000461)	(0.000991)	(0.000220)	(0.000316)	(0.000245)	(0.000193)	(0.000186)
Occupation FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	No	Yes	No
Ethnicity FE	No	No	No	Yes	No	No	Yes
PUMA FE	No	No	No	No	Yes	Yes	Yes
Occupation*Year FE	No	No	Yes	No	No	No	No
Occupation*Ethnicity FE	No	No	No	Yes	No	No	No
Occupation*PUMA FE	No	No	No	No	Yes	No	No
Occupation*PUMA*Year FE	No	No	No	No	No	Yes	No
Occupation*PUMA*Ethnicity FE	No	No	No	No	No	No	Yes
Observations	275427	275427	275427	275427	274986	242493	273211

Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results: Prediction 2

Table: Positive Difference Only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Difference_{2005}	2.010***	0.172***	0.234***	0.209***	0.0179	0.0823	0
	(0.0883)	(0.0552)	(0.0580)	(0.0587)	(0.0768)	(0.104)	(.)
POST	-0.000268	-0.000790	0	-0.000766	-0.000925	0	-0.000750
	(0.000923)	(0.000795)	(.)	(0.000792)	(0.000850)	(.)	(0.000786)
(POST)*(Difference_{2005})	0.143*	0.167**	0.0450	0.162**	0.170**	0.0453	0.158**
	(0.0858)	(0.0724)	(0.0825)	(0.0720)	(0.0773)	(0.143)	(0.0722)
High Layoffs	-0.00683***	0.000267	0.000313	-0.000302	0	0	0
	(0.00152)	(0.00116)	(0.00117)	(0.00116)	(.)	(.)	(.)
High Layoffs*(Difference_{2005})	-0.468***	0.265**	0.143	0.301**	0.286	0.129	0
	(0.172)	(0.134)	(0.134)	(0.134)	(0.200)	(0.260)	(.)
(POST)*(High Layoffs)	-0.000126	0.000251	0.000168	0.000205	0.000550	0	0.000410
	(0.00170)	(0.00160)	(0.00162)	(0.00160)	(0.00176)	(.)	(0.00160)
(POST)*(High Layoffs)*(Difference_{2005})	-0.532***	-0.516***	-0.273	-0.503***	-0.532***	-0.326	-0.530***
	(0.192)	(0.182)	(0.182)	(0.182)	(0.201)	(0.344)	(0.184)
Constant	0.0171***	0.0150***	0.0319***	0.0320***	0.0339***	0.0328***	0.0348***
	(0.000947)	(0.00159)	(0.000530)	(0.000652)	(0.000763)	(0.000752)	(0.000270)
Occupation FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	No	Yes	No
Ethnicity FE	No	No	No	Yes	No	No	Yes
PUMA FE	No	No	No	No	Yes	Yes	Yes
Occupation*Year FE	No	No	Yes	No	No	No	No
Occupation*Ethnicity FE	No	No	No	Yes	No	No	No
Occupation*PUMA FE	No	No	No	No	Yes	No	No
Occupation*PUMA*Year FE	No	No	No	No	No	Yes	No
Occupation*PUMA*Ethnicity FE	No	No	No	No	No	No	Yes
Observations	125389	125389	125389	125387	125049	78745	124486

Clustered standard errors in parentheses.

Results: Prediction 2

Table: Negative Difference Only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Difference_{2005}	-2.799***	-0.0779	-0.246***	0.0280	-0.0134	-0.0241	0
	(0.0936)	(0.0820)	(0.0858)	(0.0853)	(0.117)	(0.150)	(.)
POST	-0.000716	-0.000921	0	-0.000843	-0.00111	0	-0.000932
	(0.000884)	(0.000884)	(.)	(0.000880)	(0.000937)	(.)	(0.000871)
(POST)*(Difference_{2005})	-0.0687	-0.150	0.179	-0.141	-0.183	-0.125	-0.156
	(0.109)	(0.109)	(0.126)	(0.109)	(0.116)	(0.237)	(0.109)
High Layoffs	-0.00600***	0.000758	0.000956	-0.0000257	0	0	0
	(0.00118)	(0.000919)	(0.000915)	(0.000928)	(.)	(.)	(.)
(High Layoffs)*(Difference_{2005})	0.976***	0.0502	0.287**	-0.0258	0.677***	0.949***	0
	(0.167)	(0.133)	(0.134)	(0.135)	(0.198)	(0.270)	(.)
(POST)*(High Layoffs)	-0.0000994	-0.000151	-0.000560	-0.000257	-0.000240	0	-0.000370
	(0.00131)	(0.00131)	(0.00130)	(0.00131)	(0.00139)	(.)	(0.00130)
(POST)*(High Layoffs)*(Difference_{2005})	0.0125	0.0327	-0.447**	0.00194	0.0116	-0.487	-0.00819
	(0.189)	(0.188)	(0.193)	(0.188)	(0.202)	(0.411)	(0.190)
Constant	0.0119***	0.0160***	0.0305***	0.0319***	0.0331***	0.0327***	0.0318***
	(0.000773)	(0.00210)	(0.000592)	(0.000732)	(0.000825)	(0.000907)	(0.000260)
Occupation FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	No	Yes	No
Ethnicity FE	No	No	No	Yes	No	No	Yes
PUMA FE	No	No	No	No	Yes	Yes	Yes
()Occupation)*(Year) FE	No	No	Yes	No	No	No	No
(Occupation)*(Ethnicity) FE	No	No	No	Yes	No	No	No
(Occupation)*(PUMA) FE	No	No	No	No	Yes	No	No
(Occupation)*(PUMA)*(Year) FE	No	No	No	No	No	Yes	No
(Occupation)*(PUMA)*(Ethnicity) FE	No	No	No	No	No	No	Yes
Observations	150038	150038	150038	150036	149647	104511	148725

Clustered standard errors in parentheses.

Envisioned ML Analysis

- **Goal**: identify predictors of occupational choice, including resonance effects.
- **Model Hypotheses**
  1. Hypothesis 1: Personal characteristics predict occupations choice in ways that are not merely mediated by expected wage (and other components of utility).
  2. Hypothesis 2: Resonance effects may be intersectional, so that combinations of characteristics matter in nonlinear ways.
- **Empirical Predictions**

  Prediction 1: Among youth (age 18-22), personal characteristics such as sex, ethnicity, and education matter for predicting occupation choice, in addition to income. $\longrightarrow$ Identify (1) determinants of wage, and (2) determinants of choice, using random forests models with 100 estimators

  Prediction 2: Different characteristics may matter for representation for different subgroups. $\longrightarrow$ Identify "interaction effects"

Take Aways

- Experience Effects: Longlasting effects of personal experiences on beliefs and risk-taking ("econ-PTSD")
  - From $y_{t,i} = f(x_{i,t})$
    to $y_{i,t} = f(x_{i,t}, A(x_{i,t-1}, x_{i,t-2}, x_{i,t-3}, \ldots x_{i,0}))$
- Resonance Effects: Longlasting effects of others' personal experiences on beliefs and risk-taking ("That could have been me.")
  - From $y_{t,i} = f(x_{i,t})$
    to $y_{i,t} = f(x_{i,t}, A(x_{i,t-1}, x_{i,t-2}, x_{i,t-3}, \ldots x_{i,0}; x_{j,t}, x_{j,t-1}, x_{j,t-2}, x_{j,t-3}, \ldots x_{j,0}); \omega_{ij})$
- Evidence from macro, labor, finance, political economy
  $\Longrightarrow$ broadly applicable to learning and choice behavior
  - Feasibility of accounting for experience effects: "Big Data" within-person
  - Welfare and policy implications: information campaigns versus exposure/experiences (cf. 2021/22 inflation experiences), spill-over to the role of media and communication: limited effect unless "experiential" (cf. reggae songs of Central Bank of Jamaica, Netflix movies).