

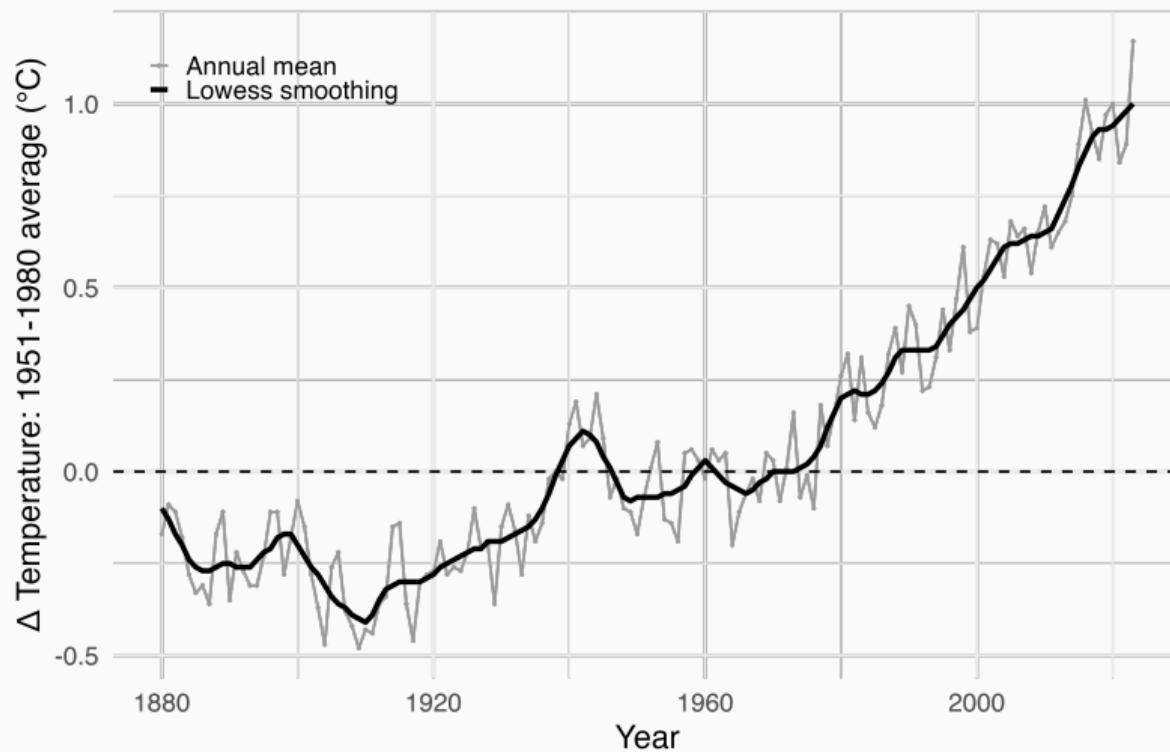
Escape the Heat: The Dynamics of Migration as Adaptation to Climate Change

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January 27, 2025

University of Arizona

It's getting hot in here...



Source: climate.nasa.gov

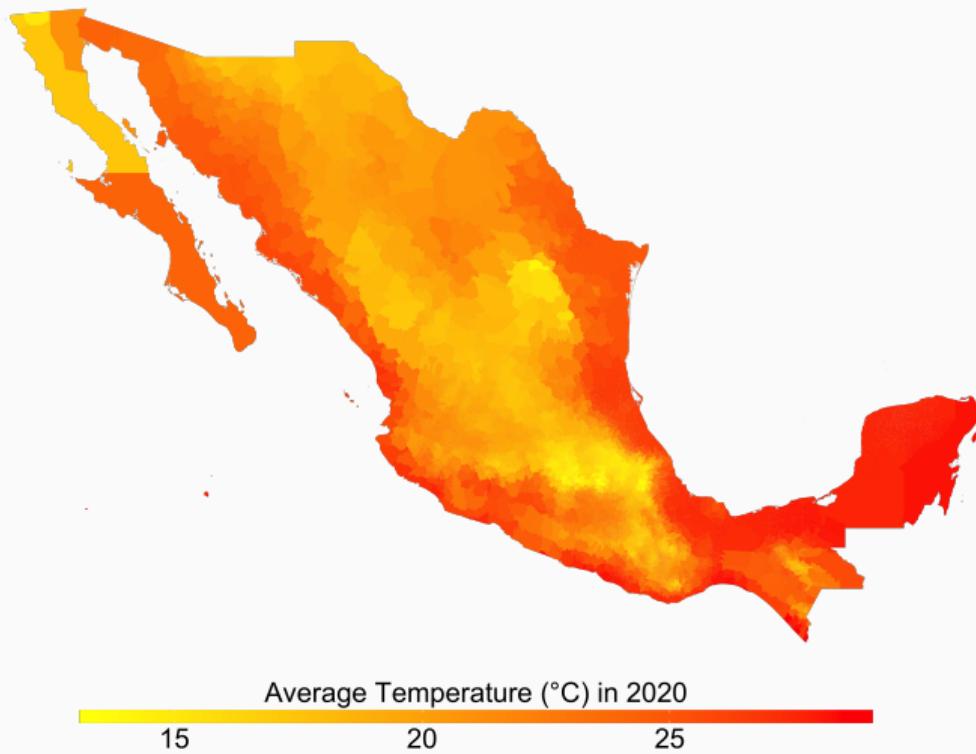
So take off... and migrate

- History suggests that human migration is a ubiquitous response to environmental change
 - 100k years ago out of Africa due to glacial changes (Timmermann & Friedrich, 2017)
 - 400 years ago through Europe due to the Little Ice Age (Waldinger, 2022)
 - Almost 100 years ago in the United States due to the Dust Bowl (Hornbeck, 2012)
- The Intergovernmental Panel on Climate Change (IPCC) has documented that an average of 21.5 million people have been displaced due to weather-related events *annually* since 2008
 - The vast majority of recent climate migration to date has been domestic (IPCC, 2022)

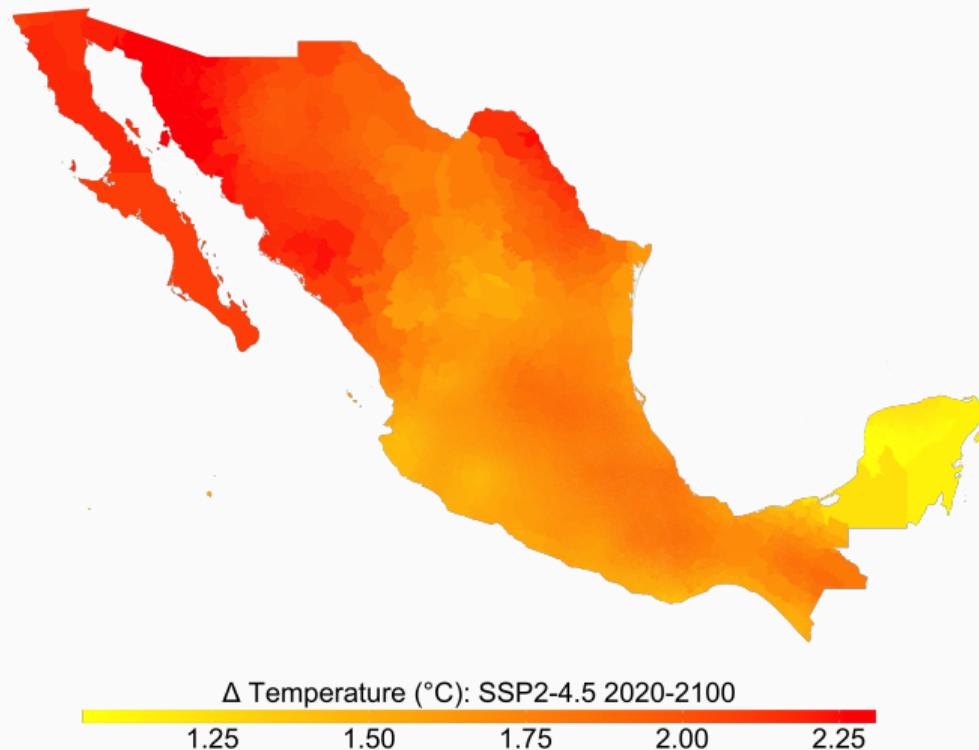
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Mexico is a large country with wide variation in local climates



The rate of warming varies strongly throughout Mexico



This paper

Questions:

- How effectively will migration limit the damages of *future* changes to the climate?
 - How sensitive are the reduced damages from migration to deviations from full information?
- How can policy be best designed to help close the “adaptation gap?”
 - What takeaways about human behavior and patience can one glean from this analysis?

Empirical approach

I combine a dynamic lifecycle model of domestic migration with a non-stationary and spatially heterogeneous model of the climate

- Estimation uses a rich panel of life histories from the Mexican Migration Project
- I estimate masses of the fully-rational and the naive surrounding the climate system

Counterfactual simulations use the estimated model and full-count census data to:

- Calculate welfare under different climate scenarios, with & without the ability to migrate
- Compare welfare across different policy options

Dynamics are needed to study migration and climate change

- Migration is a decision with dynamic consequences
- Separating the value of migration from the decision to migrate is difficult
 - Roy (1951), Borjas (1987), Dahl (2002)
- Weather \neq Climate
 - Panel models relating weather to migration identify the effect of an unexpected shock
 - Dynamic forms of adaptation are based on longer run expectations
 - Auffhammer et al. (2013), Dell et al. (2014), Lemoine (2024)
- Allowing for forward-looking expectations of future climate is important
 - Imposing naive expectations (of the climate) on the population would lead to underestimates of migration rates and overestimates of expected climate damages

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The structure allows for rich counterfactuals

I combine the estimated model with full-count census data to simulate individual decisions, across the remainder of their lifetime, for the entire male population of Mexico

The structure allows for:

- Comparisons of decisions and welfare under business-as-usual warming (climate change with current policies, BAU) to a limited warming scenario (same as 1950–1979), with and without the ability to move, for both the fully-informed and the naive
- Comparisons of potential policy options
 - Dynamic vs. static changes to moving costs

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Accounting for adaptation is important when calculating climate damages

Lifetime welfare is calculated when an individual make their first choice:

- New workers today: 17–19-year-olds in 2020 make their first choice in 2020
- Children born today: 0–2-year-olds in 2020 make their first choice in 2038

Domestic migration is an important tool for limiting climate damages

- New workers today: $\mathbb{E}[\text{lifetime climate damages}]$ are 28% lower because of migration
- Children born today: $\mathbb{E}[\text{lifetime climate damages}]$ are 33% lower because of migration

Business-as-usual warming $\Rightarrow \uparrow$ lifetime value of the ability to migrate of over 70%

- New workers today: Lifetime value of migration is $> 3 \times \uparrow$ than under limited warming
- Children born today: Lifetime value of migration is $> 6 \times \uparrow$ than under limited warming

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Correct information is valuable when dynamically adapting to climate change

The climate-naive stand to face 2% more damages ($\sim \$1,100$) from climate change

- Naivety \Rightarrow a reduced migration propensity rather than mistakes during a move (3x)
- This reduced propensity is 2.5x more costly than mistakes made during a move

Migration subsidies can serve as a nudge to the climate naive

- Dynamically-available subsidies reduce the gap b/w the belief types by 19%
- Statically-available subsidies reduce the gap b/w the belief types by 8%

Dynamic policies positively select from the population marginal to a static policy

- This additional value is present in many common policies: provisions of the IRA and first-time homeowners tax credits are examples

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Literature

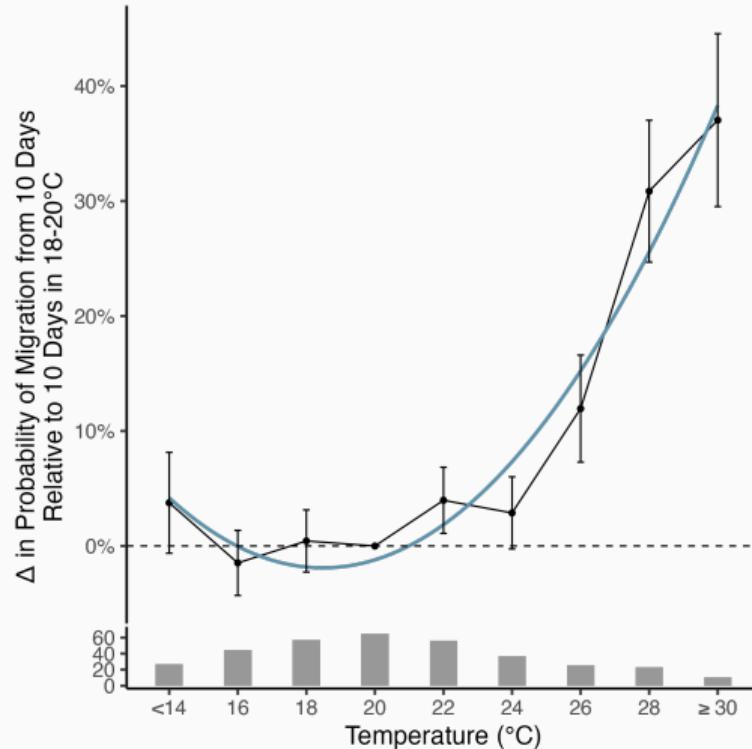
- What are the damages of climate change?
 - Reduced form: Schlenker & Roberts (2009), Burke et al. (2015), Carleton et al. (2022)
 - Spatial: Rudik et al. (2022), Bilal & Rossi-Hansburg (2023), Cruz & Rossi-Hansburg (2023)
- What are the origins of the observed “adaptation gap?”
 - Carleton & Hsiang (2016), Zappalà (2024)
- What are the welfare effects of migration?
 - Reduced form: Deryugina et al. (2018), Nakamura et al. (2022), Sarvimäki et al. (2022)
 - Structural: Kennan & Walker (2011), Oswald (2019), Ransom (2022)

Data & Empirical Motivation

I use rich microdata

Data Source	Purpose	Years
<i>Mexican Migration Project (MMP)</i>	Estimation (11,194 Life-histories)	1950–2019
<i>ENIGH, ENE surveys</i>	Estimation (Income)	1984–2019
<i>Linveh et al. (2015)</i>	Estimation (Weather)	1930–1979
<i>Daymet</i>	Estimation (Weather)	1980–2019
<i>NASA NEX-GDDP CMIP6</i>	Estimation/Simulations (Weather)	2020–2100
<i>Mexican full-count Census</i>	Simulations	2020

There is a nonlinear relationship between migration and daily temperature



Conditional on expected wages, age, person, and state-year fixed effects

The structural model builds on important patterns in the data

- Shocks to mean temperature and extreme daily temperatures, across geography and personal experience, correlate with migration decisions [Table](#)
 - Extreme temperature shocks correlate with migration decisions when living both in and out of one's birth location [Table](#)
 - This relationship persists even when comparing the average number of degree days an individual faces in a given location in the years they migrate to the years they do not [Table](#)
- Individuals seem to be forward looking over temperature when deciding to migrate [Table](#)
- Individuals consider the weather of their destination when choosing whether and where to move [Static Logit Table](#)

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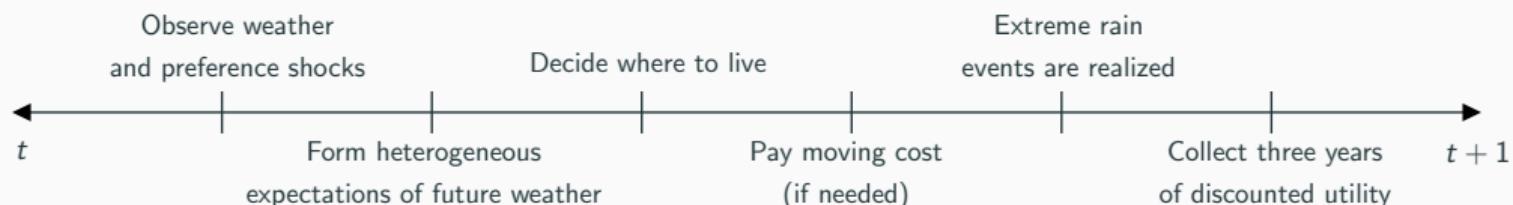
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Model

Migration is modeled as a decision with dynamic consequences

- Individuals are modeled to make the decision of where to live in Mexico
 - This decision is made every three years
 - The first decision is made at 17 years old
 - Retirement occurs at 62 years old
- I allow for four unobserved types of individuals
 - Those who are willing to move and those who are not
 - Fully-informed or naive in their expectations of the climate system



The problem can be written as a finite-horizon Bellman

At time $t < T$, individual i , of unobserved type τ , living in ℓ with state ω chooses between locations $k \in \{1, \dots, K\}$, after forming expectations for extreme rain (R), faces a Bellman:

$$V_t(\ell, \omega; \theta, \tau) = \max_k \left\{ \mathbb{E}_R[u(\ell, k, \omega, r; \theta, \tau)] + \varepsilon_{tk} + \delta^3 \mathbb{E}_{\Omega, \varepsilon|\tau}[V_{t+1}(k, \omega'; \theta, \tau)|\omega] \right\},$$

At time T , this individual's value function is instead:

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Individuals receive flow utility from living in a location

$$\begin{aligned}\bar{u}(\ell', \omega, r; \theta) = & \theta_1 \text{inc}(\ell', \omega, r) \\ & + \theta_2 DD26(\ell', \omega) + \theta_3 DD26(\ell', \omega)^2 + \theta_4 DD14(\ell', \omega) + \theta_5 DD14(\ell', \omega)^2 \\ & + \theta_6 \mathbb{1}\{\ell' = \nu^\ell\} + \theta_7 \mathbb{1}\{\ell' \in \mathcal{U}\}\end{aligned}$$

- Expected income, inc , is a function of individual and location-specific characteristics
- $DD26$: Annual degree days above 26°C $\left(\sum_{d=1}^{365} \mathbb{1}\{\overline{\text{temp}}_d \geq 26\} (\overline{\text{temp}}_d - 26) \right)$
- $DD14$: Annual degree days below 14°C $\left(\sum_{d=1}^{365} \mathbb{1}\{\overline{\text{temp}}_d \leq 14\} (14 - \overline{\text{temp}}_d) \right)$
- $\mathbb{1}\{\ell' = \nu^\ell\}$: Is ℓ' their location of birth?
- $\mathbb{1}\{\ell' \in \mathcal{U}\}$: Is ℓ' an urban location?

Wages are a flexible function of individual and environmental variables

$$\begin{aligned} \text{inc}(\ell', \omega, r) = & \sum_a \sum_e \beta_{a,e} + \beta_{ag} ag(\omega) \\ & + \sum_{c=1}^3 \left[\beta_c^{GDD,C} GDD(\omega) + \beta_c^{GDD2,C} GDD(\omega)^2 + \beta_c^{D,C} D(r) + \beta_c^{I,C} I(r) \right] \\ & + \sum_{ag=0}^1 \left[\beta_{ag}^{GDD,Ag} GDD(\omega) + \beta_{ag}^{GDD2,Ag} GDD(\omega)^2 + \beta_{ag}^{D,Ag} D(r) + \beta_{ag}^{I,Ag} I(r) \right] \\ & + \xi_{\ell'} + \eta_y(\omega) \end{aligned}$$

- GDD : Maíz growing degree days $\left(\sum_{d=1}^{365} \mathbb{1}\{8 \leq \overline{\text{temp}}_d \leq 32\} (\overline{\text{temp}}_d - 8) + \mathbb{1}\{\overline{\text{temp}}_d > 32\} 24 \right)$
- D : Drought realization
- I : Flood realization

If individuals move, they have to pay an upfront cost

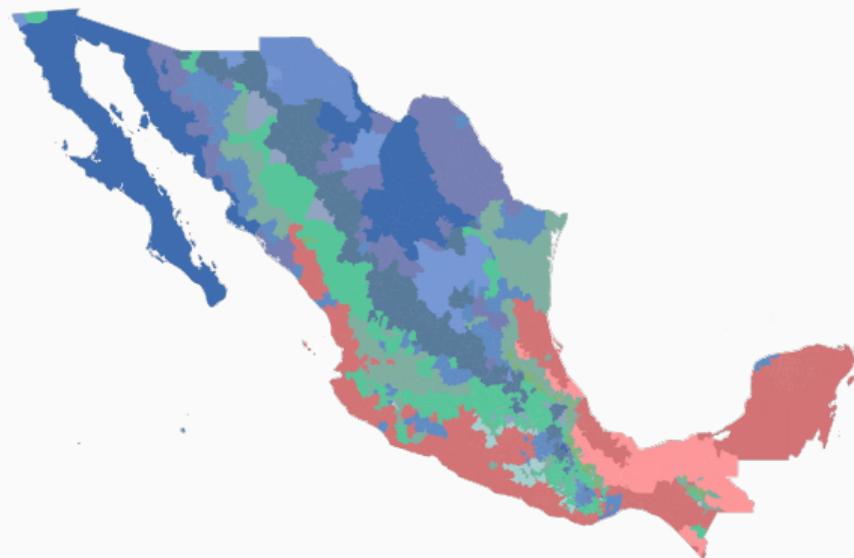
$$\bar{c}(\ell, \ell', \omega; \theta, \tau) = \gamma_1(\tau) + \gamma_2 d(\ell, \ell') + \gamma_3 \mathbb{1}\{k_\omega \geq 1\} + \gamma_4 \text{age}_\omega$$

- $\gamma_1(\tau)$: $\gamma_1(\text{mover}) \in \mathbb{R}$, $\gamma_1(\text{stayer}) \approx \infty$
- $d(\ell, \ell')$: Distance between the largest city in ℓ and ℓ'
- k_ω : Individual's number of children
- age_ω : How old is the individual?

Individuals choose from a set of 27 locations in Mexico

The choice set is composed of:

- 14 Köppen climate zones
 - INEGI modified to account for local idiosyncrasies (García, 2004)
- Urban-Rural Classification
 - INEGI Metro zones



The climate is a high-dimensional system

Past work has found that heat generally affects economic outcomes nonlinearly

- Schlenker & Roberts, 2009; Aragón et al., 2021; Miller et al., 2021

Precipitation is also generally of first-order concern for agriculture

- Deschênes & Greenstone, 2007; Seo & Mendelsohn, 2008; Dell et al., 2014

The dynamic structure of the model requires that this information be summarized concisely

- I exploit the nested structure of the Köppen climate system to reduce the number of locations whose weather I need to track down from 27 to 3
- I use a set of first-stage estimates to reduce the number of weather variables I need to track, per-location, from 5 to 2
- This allows me to use information from 141 distinct weather variables in the dynamic model, while avoiding the curse of dimensionality

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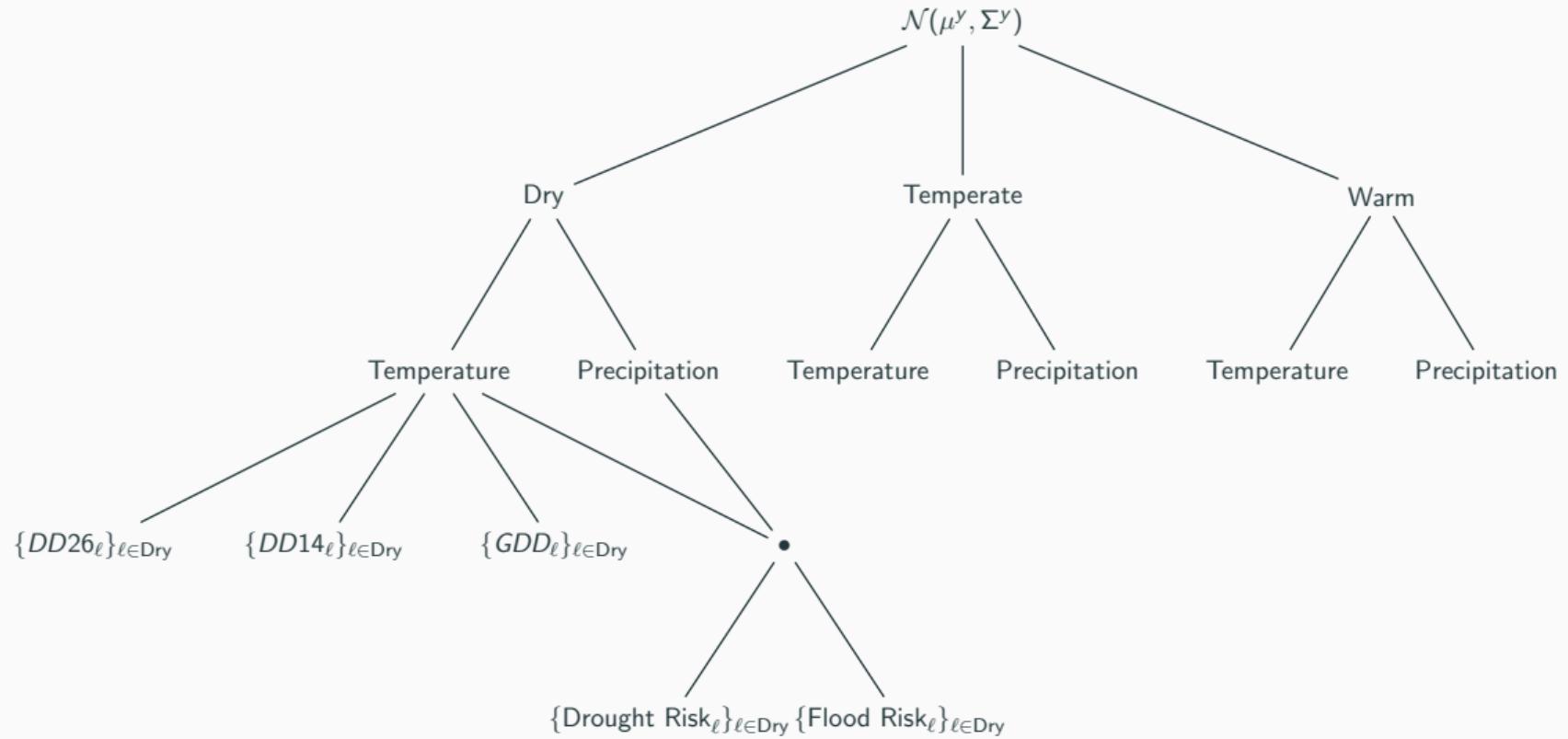
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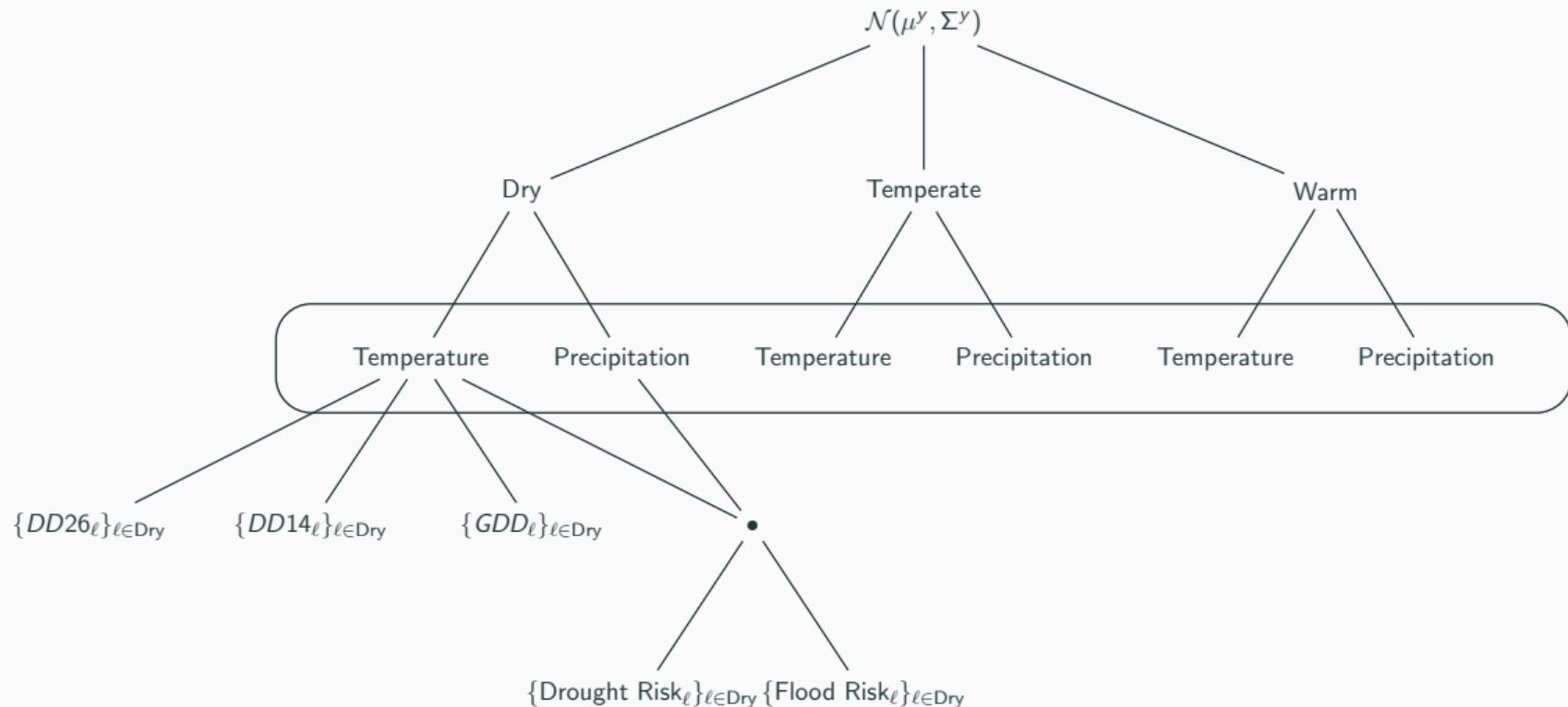
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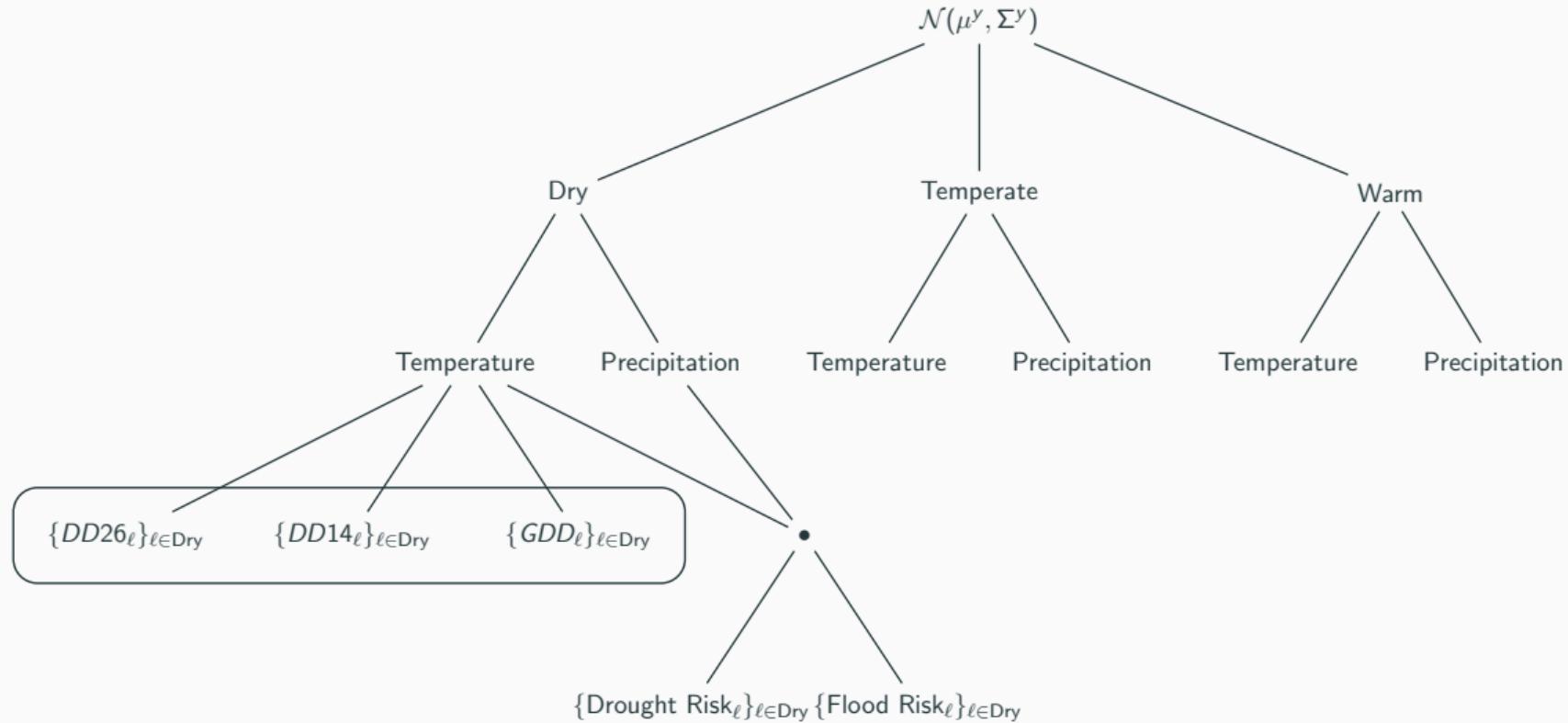
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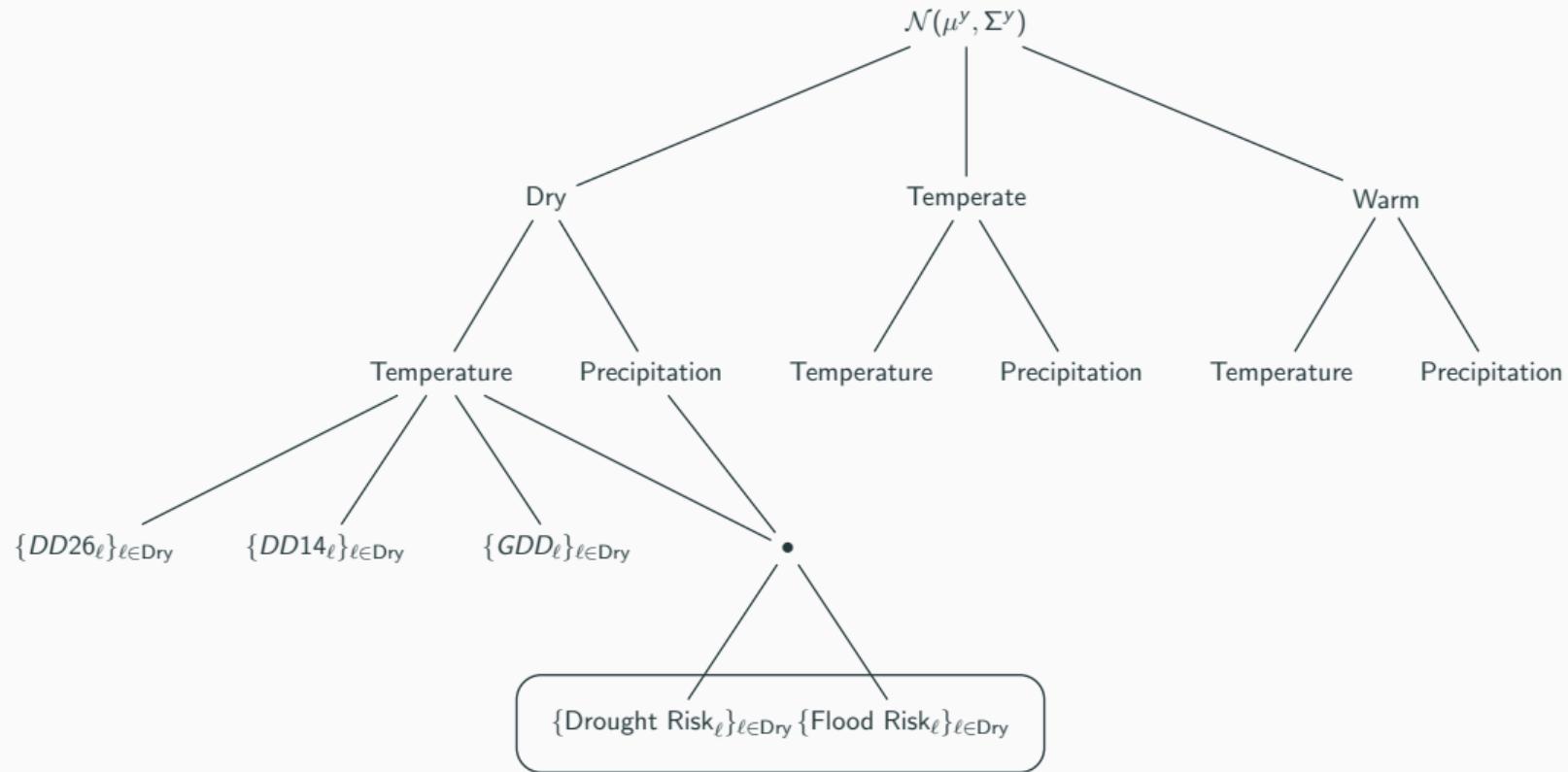
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A summary of the climate model



A summary of the climate model



The climate varies spatially and temporally

The climate evolves according to:

$$\begin{pmatrix} \text{temp} \\ \text{prec} \end{pmatrix} \sim \mathcal{N}(\mu^y, \Sigma^y),$$

Where:

$$\mu_w^y = \alpha_w^y + \alpha_{w1}^y \mu_w^{y-1} + \alpha_{w2}^y y,$$

And fully-informed individuals, in year y , use
the last 30 years of weather to obtain $\hat{\Sigma}^y$ & $\hat{\Sigma}^y$



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The climate evolves according to:

$$\begin{pmatrix} \text{temp} \\ \text{prec} \end{pmatrix} \sim \mathcal{N}(\mu^y, \Sigma^y),$$

Where:

$$\mu_w^y = \alpha_w^y + \alpha_{w1}^y \mu_w^{y-1} + \alpha_{w2}^y y,$$

And fully-informed individuals, in year y , use
the last 30 years of weather to obtain $\hat{\alpha}^y$ & $\hat{\Sigma}^y$



A model of heterogeneous climate expectations in Mexico

Fully-informed individuals use the average daily temperature to calculate the expected number of each measure of degree days in each location:

$$DD_\ell = \mathbb{1}\{\lambda_\ell^D + \lambda_{1\ell}^D \text{temp}_{C(\ell)} > 0\} \times [\lambda_\ell^D + \lambda_{1\ell}^D \text{temp}_{C(\ell)}], \quad (1)$$

They use realized agricultural-season precipitation (P) to calculate drought and flood risk:

$$\text{prob}(R_\ell) = \Phi\left(\eta_\ell^R + \eta_1^R P_{C(\ell)} + \eta_2^R \text{temp}_{C(\ell)}\right), \quad (2)$$

Individuals who form naive climate expectations are only assumed to observe the current years' weather and to assume that all future years will be the same

Estimation & Identification

I estimate the primitives using a full solution maximum likelihood routine

Initial Step: Estimate distribution of state variable transitions, the wage equation, and the climate mappings

Inner Loop: Solve the Bellman using backward recursion across t to form model-induced choice probabilities

Outer Loop: Maximize log likelihood

The likelihood is a finite mixture

The log-likelihood is given by:

$$\begin{aligned}\Lambda(\theta, \pi) &= \sum_i \log (\mathbb{E}_\tau [\mathcal{L}_i(\theta; \tau)]) \\ &= \sum_i \log \left(\sum_\tau \pi_\tau \cdot \mathcal{L}_i(\theta; \tau) \right),\end{aligned}$$

Where:

$$\mathcal{L}_i(\theta; \tau) = \prod_{t=1}^{T_i} \mathcal{L}_{it}(\theta; \tau) = \prod_{t=1}^{T_i} \frac{\exp(\bar{V}_t(\ell_{it}, \ell_{it+1}, \omega; \theta, \tau))}{\sum_{j \in \mathcal{C}} \exp(\bar{V}_t(\ell_{it}, j, \omega; \theta, \tau))},$$

And, π_τ is the probability of being of type τ $\left(\sum_{\tau=1}^4 \pi_\tau = 1\right)$

Results

Parameter estimates

Description	Parameter	Coefficient	Std. Error
Flow utility			
Income, measured in 2010 hourly pesos	θ_1	0.006	(0.0007)
Degree days above 26°C	θ_2	0.034	(0.005)
Degree days above 26°C squared	θ_3	-0.015	(0.002)
Degree days below 14°C	θ_4	0.020	(0.002)
Degree days below 14°C squared	θ_5	-0.003	(0.0003)
Living in location of birth	θ_6	0.183	(0.002)
Living in an urban location	θ_7	-0.041	(0.003)
Moving costs			
Fixed migration cost, for movers	γ_1	2.599	(0.073)
Distance of move	γ_2	0.140	(0.011)
Cost shifter: parenthood	γ_3	0.072	(0.022)
Cost shifter: age	γ_4	0.172	(0.006)
Unobserved heterogeneity			
Mass of movers	π_m	0.628	(0.013)
Mass of fully-informed expectations	π_b	0.673	(0.206)

Notes: Distance is measured in log kilometers. The likelihood contains 90,578 individual-year observations from 11,194 individuals. Asymptotic standard errors are calculated using the score of the likelihood.

Understanding magnitudes

- Individuals are indifferent between living in their location of birth and living away from this location with about twice the average annual income
- Negative preference for living in an urban location
 - Evidence of a compensating differential for living in urban centers (Rosen, 1986)
- Estimated average moving cost is very large ($\sim \$99k$)
 - This is the average cost of a forced move in an arbitrary period to an arbitrary location
 - Kennan & Walker (2011) style calculations show that actual costs paid are on average negative ($\sim \$-50k$) and positive for moves back home ($\$29k$)

Understanding magnitudes

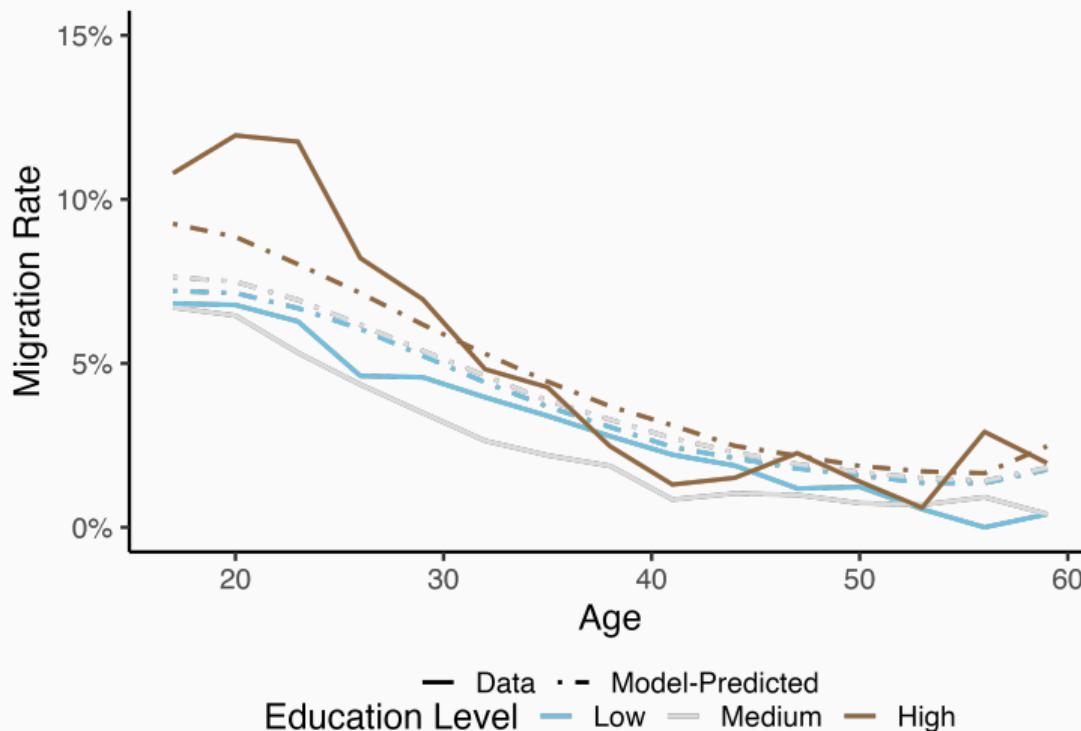
I estimate a bliss-point of 113 degree days above 26°C

- Historically, 16% of the population experienced heat beyond this level
- In 2050, 49% of the population would experience heat beyond this level, w/o migration

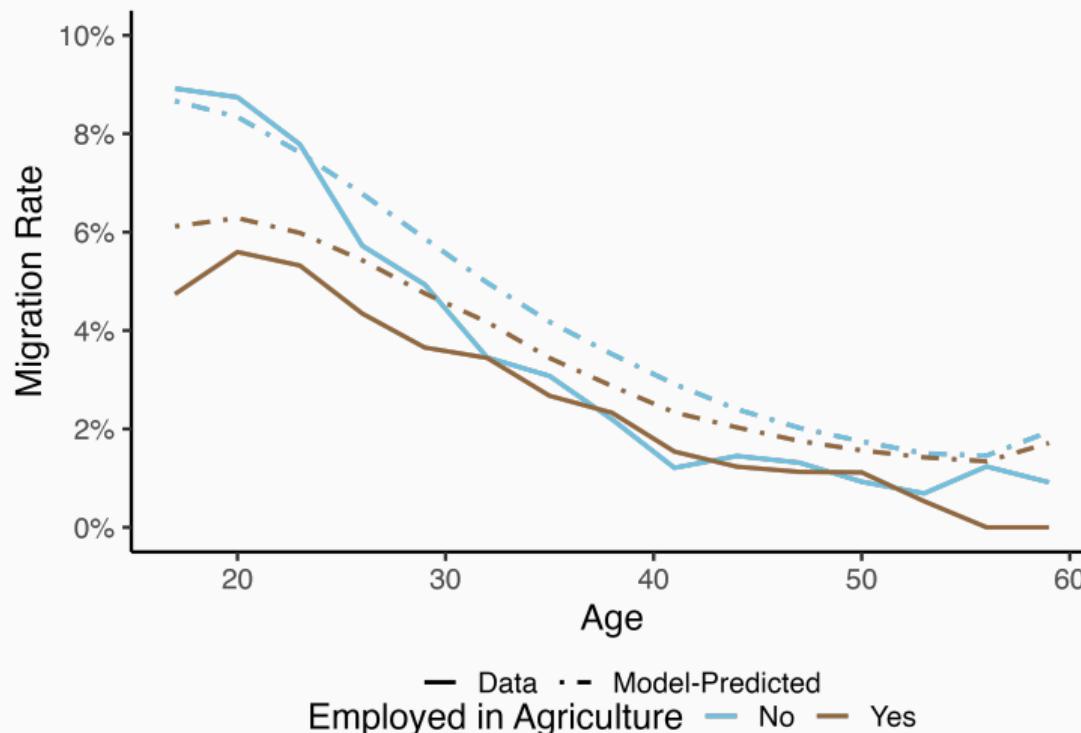
I estimate a bliss-point of 333 degree days below 14°C

- Historically, 9% of the population experienced cold beyond this level
- In 2050, 0.02% of the population would experience cold beyond this level, w/o migration

The model fits the data well across levels of education



The model fits the data well across sectors of employment



Simulations

I use the model to simulate choices under different environments

- I use the 2020 Mexican Census to obtain:
 - Number of individuals, by age, living in each municipality
 - Percent of individuals, by municipality, employed in agriculture
 - Distribution of education by municipality
- Simulate different climate scenarios with and without the ability to move
 - Use daily data from CMIP6 SSP2 4.5 scenario to simulate business-as-usual climate
 - Use historical data to simulate limited warming as a counterfactual scenario of the climate system centered around 1950-1979 averages
- Simulate the decisions of individuals under the different scenarios
 - Bring new young men into the model based on census counts for children
 - Retire people at 62 years old

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What is the lifetime value of migration?

The lifetime value of the ability to migrate, at year y , can be calculated as the average difference in welfare across counterfactual simulations, with and without the ability to migrate, amongst those who are 17–19-years-old in y . Mathematically,

$$\frac{1}{n(y)} \sum_{i(y)} \left\{ \tilde{V}(\ell_i, \omega_i | s) - \tilde{V}(\ell_i, \omega_i | s, \gamma_1 = \infty) \right\}.$$

- $\tilde{V}(\cdot)$: Value function, scaled to 2024 dollars
- γ_1 : Fixed moving cost
- i indexes individuals making their first migration decision in year y ($|i| = n_y$)

Translation from utils to dollars

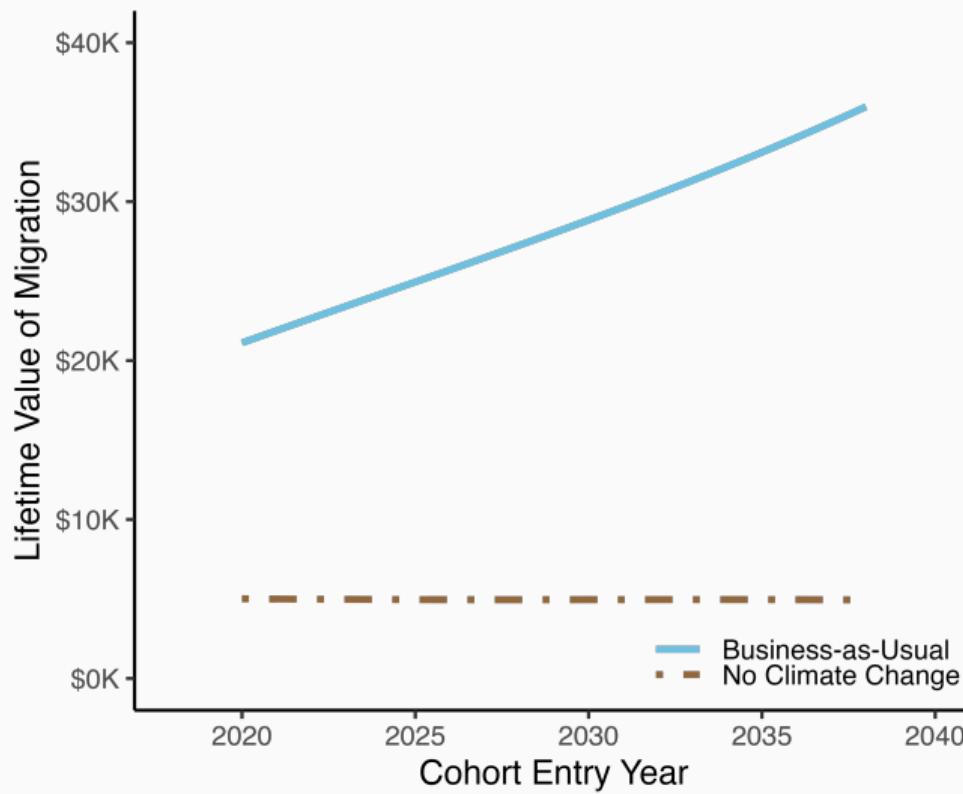
Accounting for congestion effects on wages

Heterogeneity in the value of migration

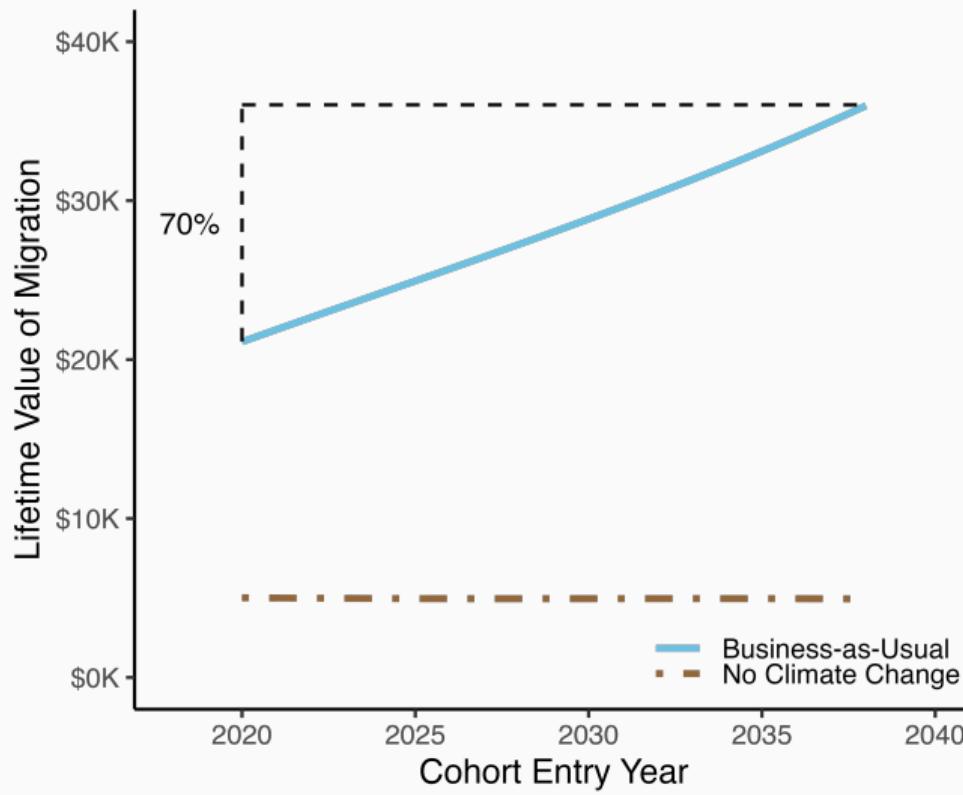
Migration rates across time and heterogeneous beliefs

Recursive derivation of naive value function

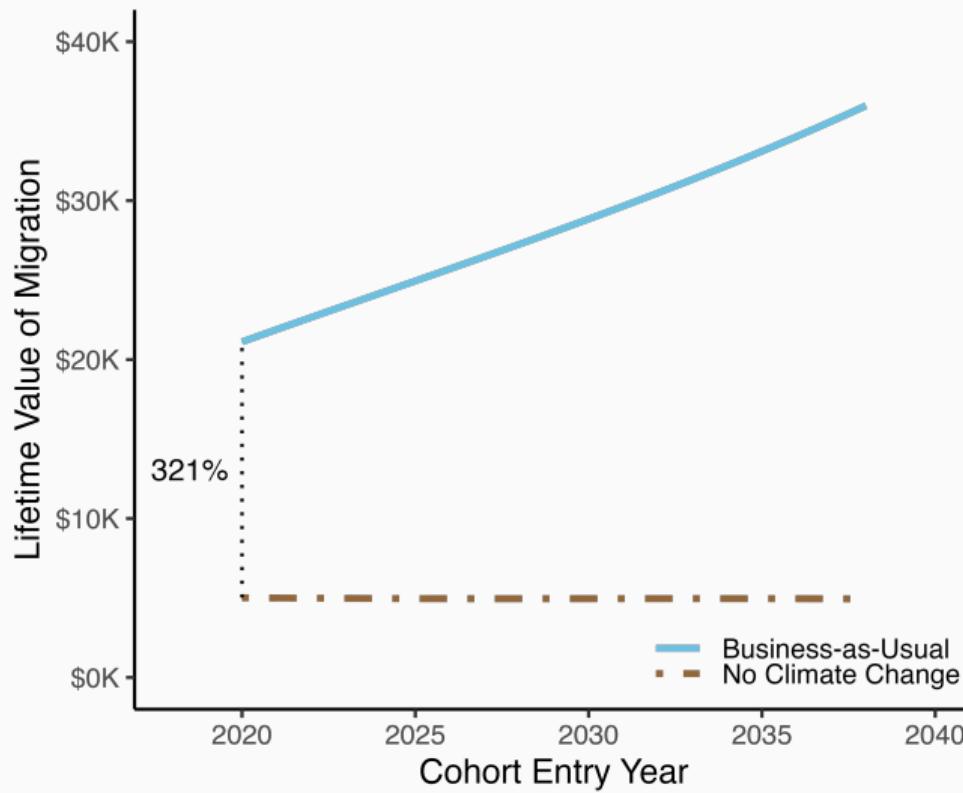
Migration becomes more valuable over time with warming



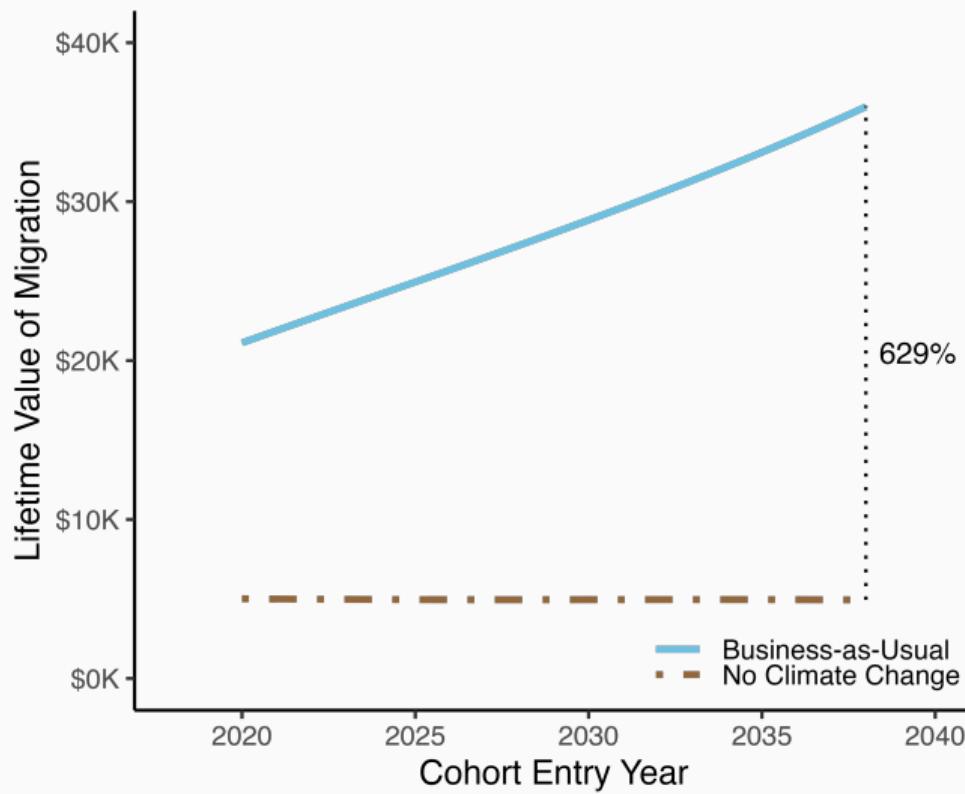
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Migration becomes more valuable over time with warming

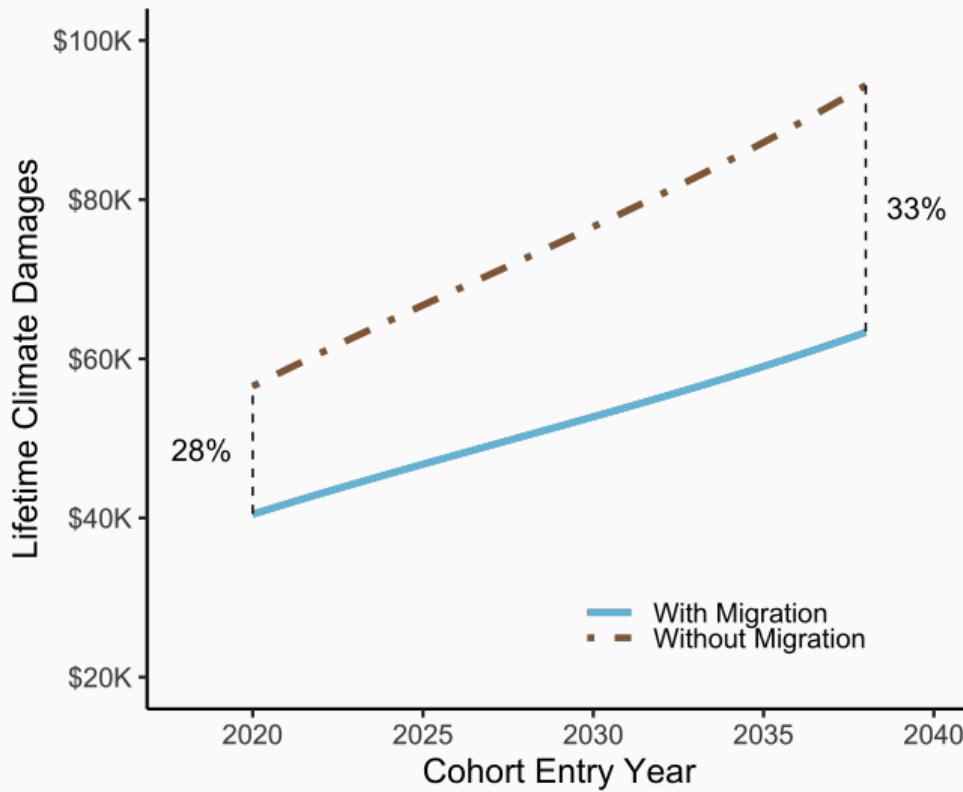


How effectively will migration limit climate damages?

Average expected lifetime climate damages can be calculated as the average difference in welfare across counterfactual simulations with and without climate change. Mathematically,

$$\frac{1}{n(y)} \sum_{i(y)} \left\{ \tilde{V}(\ell_i, \omega_i | \text{no cc}) - \tilde{V}(\ell_i, \omega_i | \text{BAU}) \right\}.$$

Migration reduces expected climate damages



Migration is progressive adaptation to regressive climate damages

Age in 2020:	% ↓ in Damages from Migration	
	17–19-years-old	<2-years-old
Average	28%	33%
Climate Figure		
Dry	27%	27%
Temperate	3%	1%
Warm	35%	40%
Agricultural Worker Figure		
Yes	32%	37%
No	28%	32%
Years of Education Figure		
0–5	32%	36%
6–11	30%	34%
12+	28%	32%

Notes: These are the average results of 100 simulations of the model.

Damages are measured in lifetime values. Climate damages are in 2024 dollars, and represent the average difference in lifetime welfare for a 17-year-old in 2020. The percentage decrease in damages from migration is the average difference in climate damages from a world without migration to one with migration.

The climate-naive face enhanced climate damages

Age in 2020:	% ↓ in Climate Damages from Info	
	17–19-years-old	<2-years-old
Average	2.2%	1.2%
Climate		
Dry	0.4%	0.6%
Temperate	1.3%	2.2%
Warm	3.2%	1.2%
Agricultural Worker		
Yes	2.9%	1.0%
No	2.1%	1.3%
Years of Education		
0–5	2.7%	1.1%
6–11	2.5%	1.2%
12+	2.1%	1.3%

Notes: These are the average results of 100 simulations of the model. Values are for 17–19 year olds, measured in 2024 dollars. The percent decrease in climate damages represents that for the climate-naive individuals from becoming fully-informed.

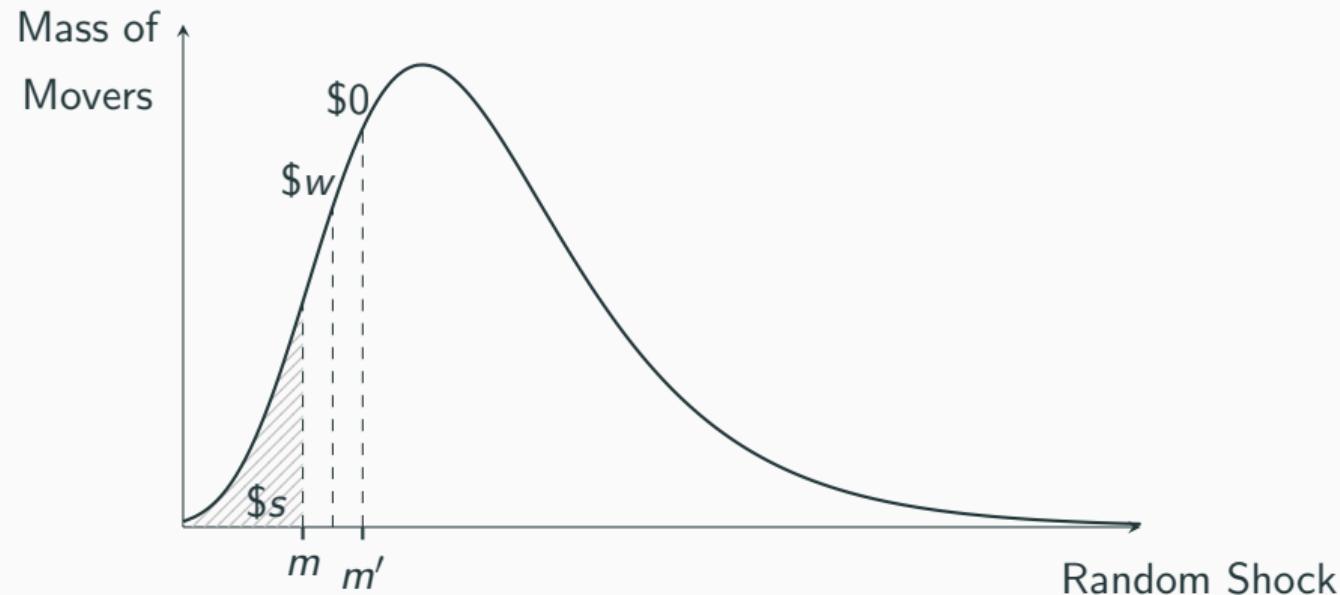
Common policy tools can reduce the size of this internality

	Value of Climate Information in 2020		
	Dollar Value	% ↓ from \$1,100 Dynamic Subsidy	% ↓ from \$1,100 Static Subsidy
	Average	1,099	18.7%
Climate			
Dry	544	29.7%	12.8%
Temperate	298	49.0%	21.4%
Warm	4,300	10.4%	4.1%
Agricultural Worker			
Yes	2,019	13.7%	5.3%
No	976	20.2%	8.6%
Years of Education			
0–5	1,700	13.7%	6.0%
6–11	1,313	18.8%	7.0%
12+	987	19.2%	8.5%

Notes: These are the average results of 100 simulations of the model.

The value of climate information refers to the difference in average lifetime welfare between the population of fully-informed and climate-naïve individuals, in 2020. The decrease in the value of climate information from a dynamic and static subsidy refers to the decrease of the dollar value of climate information from a one-time \$1,100 subsidy to be used at the first time an individual moves and a take-it-or-leave-it offer, both in 2020.

Intuition for the differences between dynamic and static policies



Notes: m is the cutoff for inframarginal movers, s is the size of the subsidy, w is the size of the option value for future moving opportunities with a subsidy of s . The shaded area is the portion of the population inframarginal to any policy.

Conclusion

Summary of findings

- The spatial heterogeneity in climate damages makes migration a highly valuable mechanism of adaptation, even within national borders
 - Accounting for adaptation when estimating climate damages is important
 - Damages could be even lower if the population understood the climate system
- Policy can play a role in helping individuals adapt to climate change
 - Migration subsidies nudge the climate-naive into behaving more similarly to the fully-informed
 - Dynamic policies generate large welfare improvements when compared to static policies
- Future work on the topic can focus on:
 - The role, and limits, of in-situ adaptation to climate change
 - The general equilibrium effects of migration as adaptation to climate change, and the role of policy

Thank You

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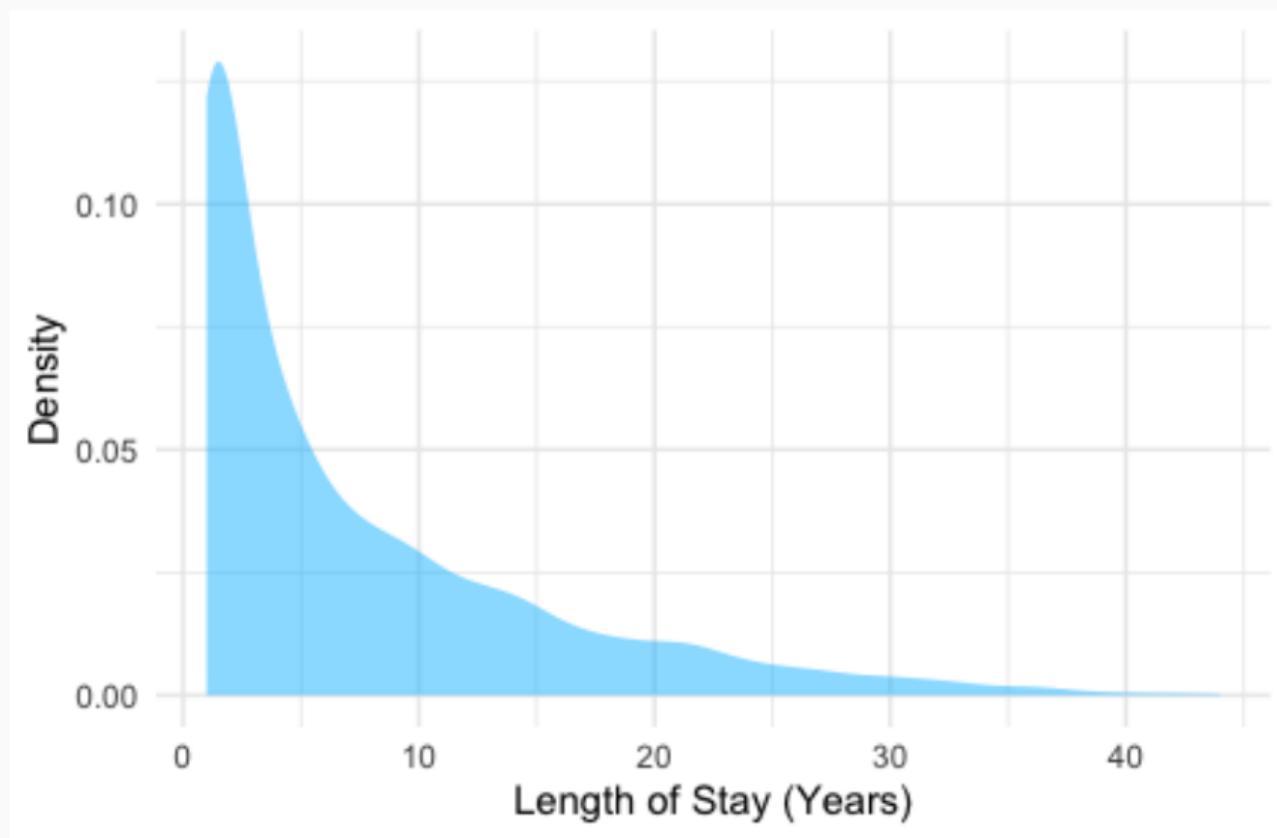
Appendix

Data: MMP

- Annual survey (since 1982) of individuals living in Mexico
- 3-5 locations are chosen each year - Not a nationally representative sample
 - Previous work has found that the MMP sample has, on average, a higher level of education, and a large oversampling of men
- Use de-censored version of life history files to construct a panel of the location of residence for ~ 12k people

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Length of Stay



Estimation - Inner Loop

1. State Space Partitioning:

- Divide the individual-specific state space into n chunks.
- Assign each of the n compute nodes its own chunk.

2. Utility Calculation:

- u is linear in parameters.
- Compute a high-dimensional tensor product of utility inputs and the vector of structural parameters.

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Estimation - Inner Loop

3. Value Function at T :

- For each location in state space, integrate out state transitions in time $T + 1$.
- Solve for \bar{V}_T .

4. Backward Induction:

- Use $\{\bar{V}_T(\omega)\}$ and 2. to calculate \bar{V}_{T-1} at each point in state space.
- Repeat until $t = 1$.

Back

	Dependent Variable: $\mathbb{1}\{\text{Migrate}\}$			
	(1)	(2)	(3)	(4)
Average Temperature	0.00143*** (0.00031)	0.00142*** (0.00033)	0.0045*** (0.0010)	0.0106*** (0.0014)
Cooling Degree Days (26)	0.0129*** (0.0017)	0.0130*** (0.0017)	0.00589*** (0.00095)	0.0149*** (0.0024)
Heating Degree Days (14)	0.00303*** (0.00059)	0.00318*** (0.00059)	0.0075*** (0.0011)	0.0083*** (0.0016)
Agricultural Worker	-0.0052*** (0.0006)			
Education	0.00084*** (0.00010)			
Children	-0.01365*** (0.00089)			
Num.Obs.	260472	260472	260472	260472
R2	0.052	0.050	0.168	0.201
FE: Year-State	X	X		X
FE: Person			X	X

Back

	Dependent Variable: $\mathbb{1}\{\text{Migrate}\}$			
	(1)	(2)	(3)	(4)
Cooling Degree Days (26)	0.0113*** (0.0014)	0.00479*** (0.00085)	0.0180*** (0.0022)	0.0043*** (0.0017)
Heating Degree Days (14)	0.00189*** (0.00039)	0.0028*** (0.0010)	-0.000027 (0.001404)	-0.0012 (0.0013)
Cooling Degree Days: Away From Birth Loc	0.0071*** (0.0021)	0.0168*** (0.0038)	0.0123*** (0.0037)	
Heating Degree Days: Away From Birth Loc	-0.00249*** (0.00065)	-0.0024 (0.0021)	-0.00029 (0.00227)	
Num.Obs.	260472	260472	260472	260472
R2	0.064	0.176	0.205	0.341
FE: Year-State	X		X	X
FE: Person		X	X	
FE: Person-Location				X

Back

	<i>Dependent Variable:</i> $\mathbb{1}\{\text{Migrate}\}$		
	(1)	(2)	(3)
Current Temperature	0.0097*** (0.0012)	0.0052*** (0.0012)	0.0011 (0.0014)
Last Year's Temperature		0.0050*** (0.0013)	0.0044*** (0.0013)
Next Year's Temperature			0.0052*** (0.0012)
Num.Obs.	260472	260472	260472
R2	0.200	0.200	0.200
FE: Year-State	X	X	X
FE: Person	X	X	X

Back

Flow Utility		Moving Costs	
Income	0.061 (0.008)	Moving Intercept	2.89 (0.161)
Cooling Degree Days (26)	0.071 (0.051)	Distance	0.139 (0.027)
Cooling Degree Days ²	-0.074 (0.015)	Children	0.130 (0.040)
Heating Degree Days (14)	0.137 (0.015)	Age	0.210 (0.009)
Heating Degree Days ²	-0.023 (0.002)		
Urban Location	-0.345 (0.011)		
Birth Location	2.452 (0.41)		

Log-Likelihood: -25255.83

Back

	Hourly Income		
Ag worker	0.74 (3.55)	Warm × GDD	-6.4 (14.6)
Growing Degree Days	7.5*** (2.8)	Temperate × GDD ²	0.75 (0.75)
Growing Degree Days ²	-0.95** (0.44)	Warm × GDD ²	0.87 (2.17)
Drought	-0.38* (0.20)	Temperate × Drought	0.77*** (0.22)
Inundation	-0.036 (0.310)	Warm × Drought	0.66** (0.33)
Ag worker × GDD	-3.0 (2.8)	Temperate × Inundation	-0.56* (0.32)
Ag worker × GDD ²	0.58 (0.52)	Warm × Inundation	-0.13 (0.36)
Ag worker × Drought	0.38 (0.25)	Num.Obs.	3626618
Ag worker × Inundation	-0.44* (0.24)	R2	0.231
Temperate × GDD	-5.1 (3.8)	FE: Location, Year	X
		Dep. Var. Mean	27.06

Back

Alternative-specific value function

$$\begin{aligned}\bar{V}_t(\ell, k, \omega; \theta, \tau) &= \mathbb{E}_R[u(\ell, k, \omega, r; \theta, \tau)] + \delta^3 \mathbb{E}_{\Omega, \varepsilon | \tau}[V_{t+1}(k, \omega'; \theta, \tau) | \omega] \\ &= \mathbb{E}_R[u(\ell, k, \omega, r; \theta, \tau)] + \delta^3 \int \max_j \{\bar{V}_{t+1}(k, j, \omega'; \theta, \tau) + \varepsilon_j\} dF_{\omega', \varepsilon | \omega, \tau} \\ &= \mathbb{E}_R[u(\ell, k, \omega, r; \theta, \tau)] + \delta^3 \int \log \left(\sum_{j \in \mathcal{C}} \exp(\bar{V}_{t+1}(k, j, \omega'; \theta, \tau)) \right) dF_{\omega' | \omega, \tau}\end{aligned}$$

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Mapping Utils to Dollars

Define some quantity u measured in utils.

1. $u_1 = \frac{u}{\theta_1}$ is measured in 2010 pesos per hour per year
 - θ_1 is measured in utils per 2010 peso per hour per year
2. $u_2 = u_1 \times \text{hours of work per year}$ is measured in 2010 pesos
 - OECD gives that this value is 2,224 hours, for the average Mexican in 2010
3. $u_3 = \frac{u_2}{e_{2010}}$ is measured in 2010 dollars
 - e_{2010} is the exchange rate on January 1, 2010: 12.8096
4. $u_4 = u_3 \times \text{inflation rate}_{2010 \rightarrow 2024}$ is measured in 2024 dollars
 - I use the CPI for all urban consumers: 1.45

General Equilibrium

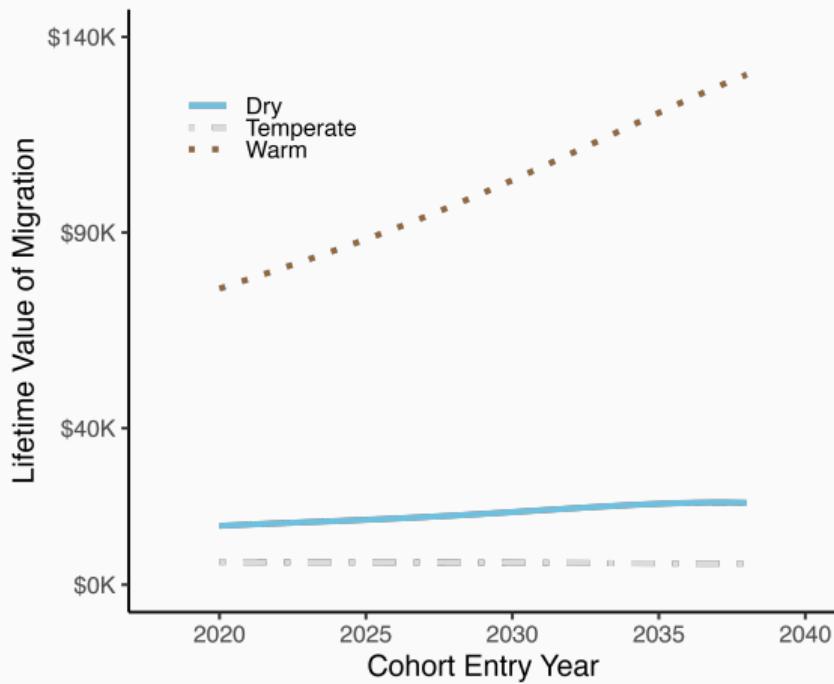
Migration is modelled in a partial equilibrium setting. I employ the following to understand how strong general equilibrium effects may be:

1. Simulate migration decisions with the estimated model and wage equation through 2038
2. Calculate the difference in population levels from 2023 to 2038 throughout Mexico
3. Assume that wages respond to this change in population
4. Resimulate behavior under the new wage regime

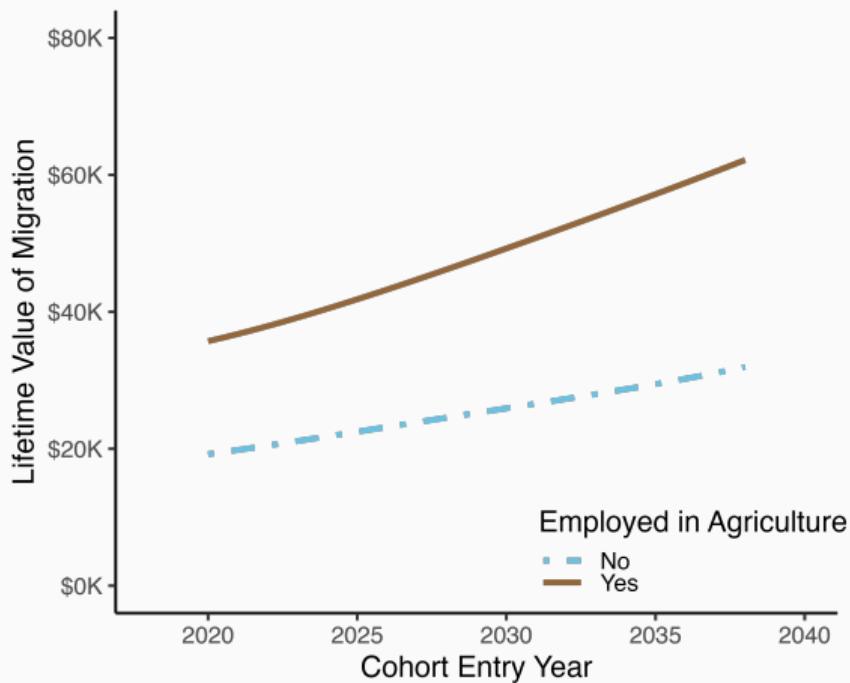
I iterate on this process until population counts converge across iterations. It takes 17 iterations to do so.

[Back](#)

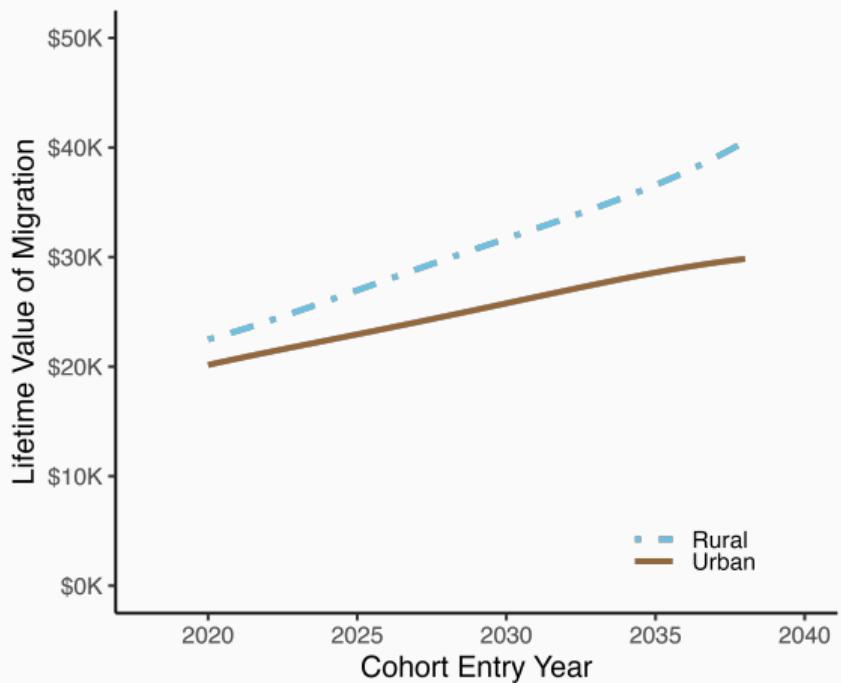
Heterogeneity in Values across Space



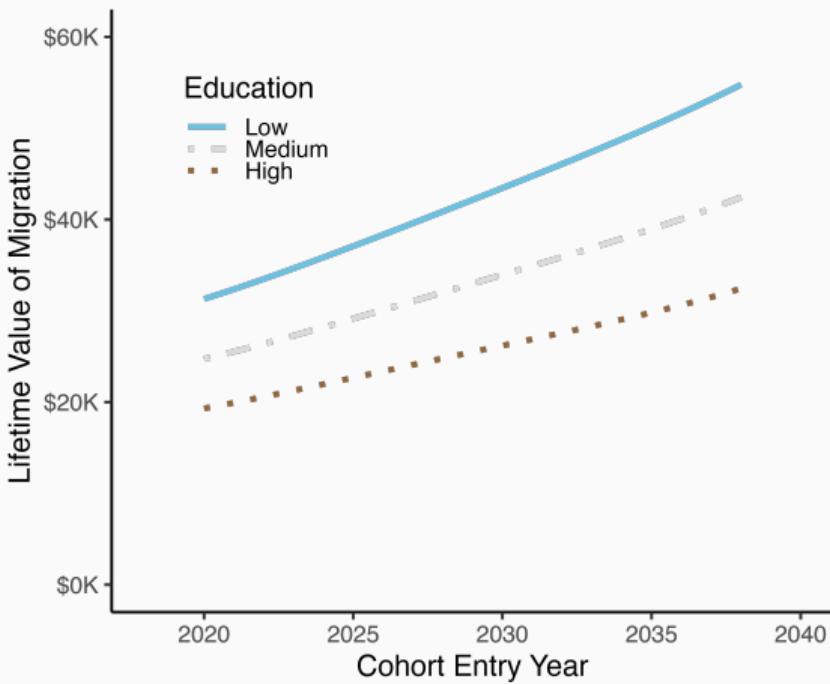
Heterogeneity in Values across Sector of Employment



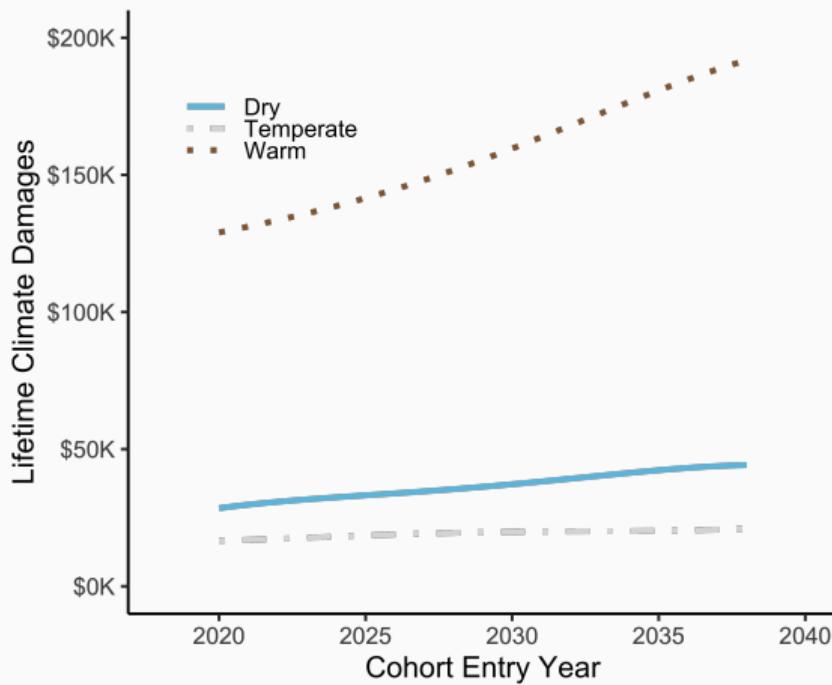
Heterogeneity in Values across Urban-Rural



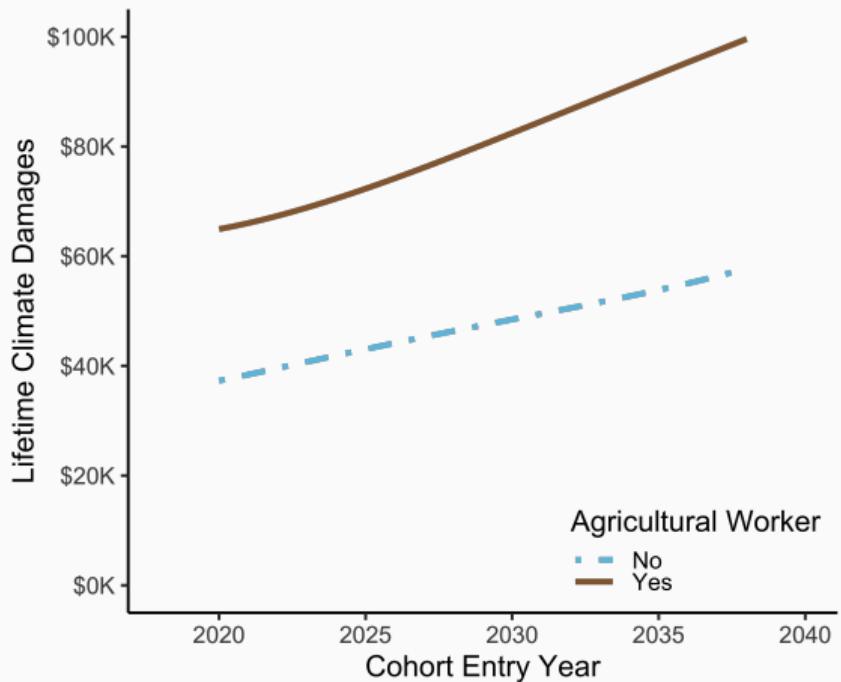
Heterogeneity in Values across Levels of Education



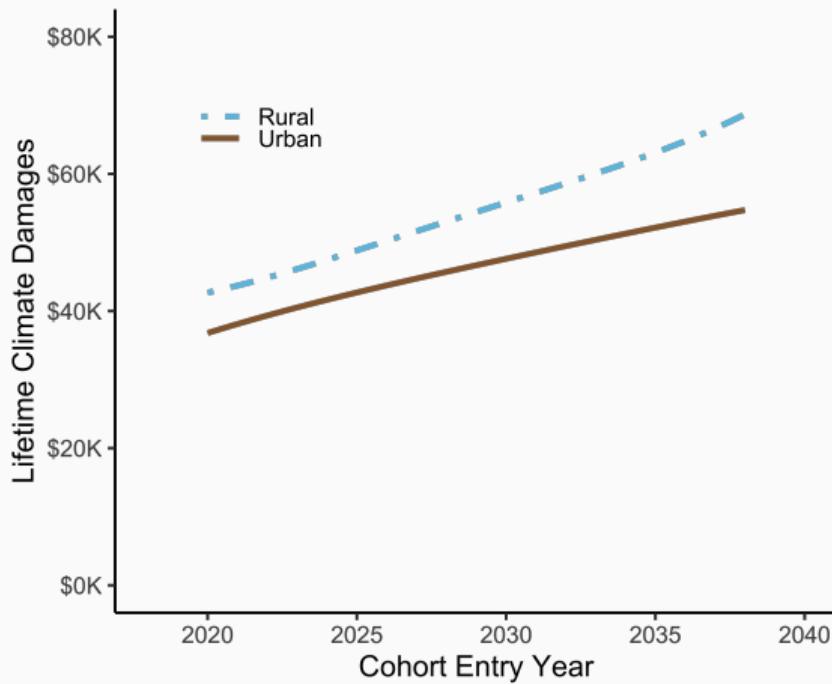
Heterogeneity in Climate Damages across Space



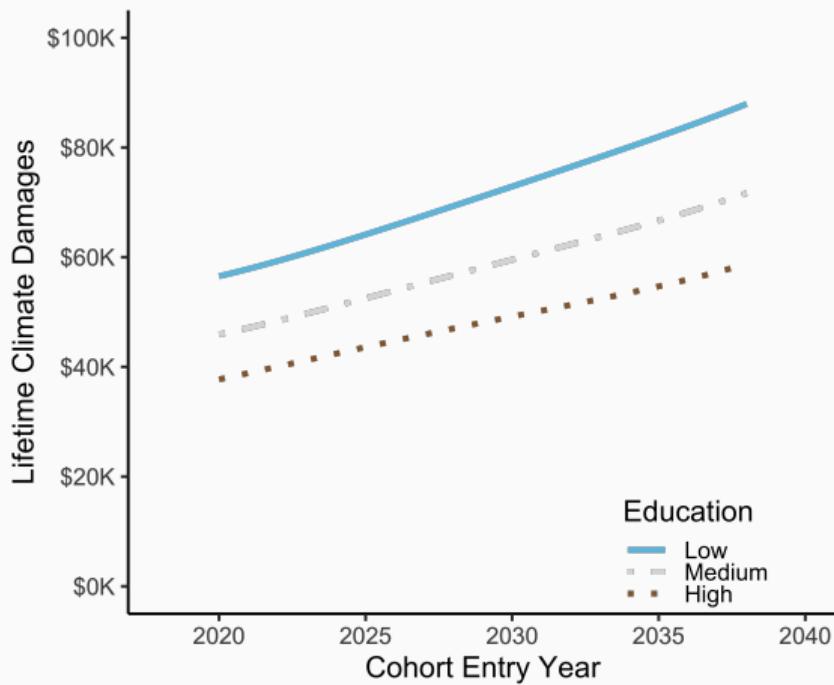
Heterogeneity in Climate Damages across Sector of Employment



Heterogeneity in Climate Damages across Urban-Rural



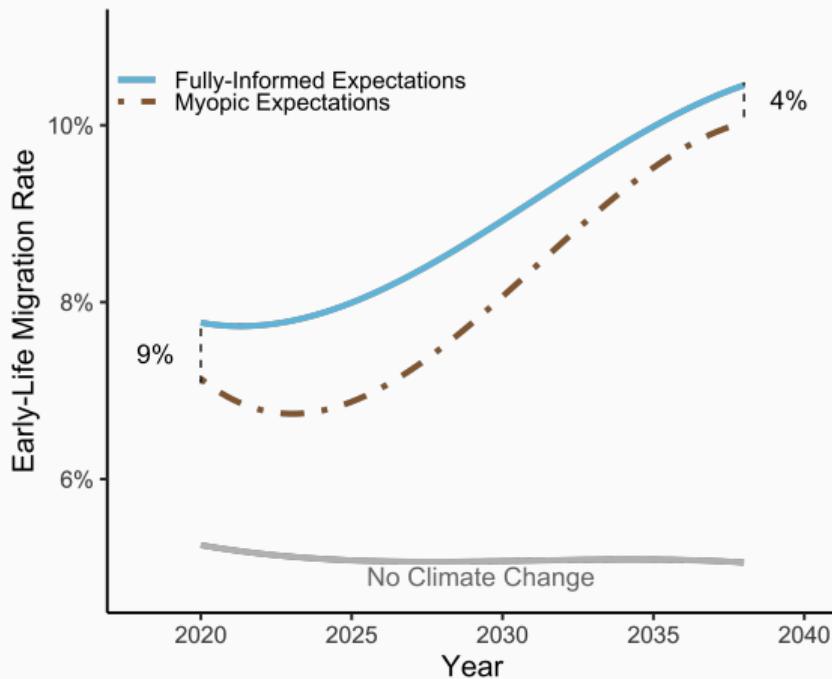
Heterogeneity in Climate Damages across Levels of Education



Summary statistics

	Non-Migrants		Migrants		2020 Census	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Education	7.66	4.25	8.76	4.96	9.03	3.63
Agricultural Worker	0.32	0.47	0.22	0.41	0.31	0.46
Children	0.95	0.21	0.93	0.26	-	-
Age at Birth of First Child	23.83	4.90	24.37	4.90	-	-
Number of Moves	-	-	2.16	1.84	-	-
Age at First Move	-	-	22.69	6.30	-	-
Move to Urban Location	-	-	0.32	0.46	-	-
$\mathbb{1}\{\text{Stay} > 1 \text{ Year}\}$	-	-	0.74	0.44	-	-
Born in Dry Climate	0.28	-	0.26	-	0.24	-
Born in Temperate Climate	0.41	-	0.48	-	0.59	-
Born in Warm Climate	0.32	-	0.26	-	0.17	-
Born in Urban Location	0.25	-	0.24	-	0.41	-
Number of Individuals	8406		2788			

Migration rates are increasing in warming



Climate Model Fit

- The location-specific mapping from primary climates to growing degree days has an adjusted- R^2 of 0.985
 - If we remove all location-specific intercepts, the adjusted R^2 is 0.640 (this only looks at within-location variation in GDD explainable from variation in the primary climate's mean temperature)
- The location-specific mapping from primary climate temperature to degree days above 26°C has a McFadden pseudo- R^2 of 0.240
- The location-specific mapping from primary climate temperature to degree days below 14°C has a McFadden pseudo- R^2 of 0.240
- The model for the likelihood of drought has a McFadden pseudo- R^2 of 0.041
- The model for the likelihood of flood has a McFadden pseudo- R^2 of 0.101

The model fits the data well

	Migration Rate	
	Model	Data
Overall	5.4%	4.7%
Children		
Yes	5.2%	3.4%
No	5.4%	7.2%
Agricultural Worker		
Yes	4.5%	3.5%
No	5.8%	5.3%
Years of Education		
0-5	5.0%	4.2%
6-11	5.3%	3.8%
12+	6.1%	7.5%

Notes: For each category, I calculate the average migration rate predicted by 100 model simulations of the life trajectories of the individual-year observations used in estimation.

Migration as adaptation to climate change is progressive

	% ↑ in the value of the ability to move, from BAU warming	
	New workers today	Children born today
Climate Figure		
Dry	128%	314%
Temperate	12%	11%
Warm	1020%	2092%
Agricultural Worker Figure		
Yes	471%	987%
No	201%	469%
Years of Education Figure		
0–5	379%	832%
6–11	280%	641%
12+	205%	480%

Notes: Shown are the percentage change in the average 2020 lifetime value of migration, of business-as-usual warming compared to limited warming, across different demographic and spatial groups. BAU represents business-as-usual: the CMIP6 SSP2 4.5 scenario.

Derivation of naive value function

$$\begin{aligned}\bar{V}_t^{nt}(\ell, \ell', \omega) &= u(\ell, \ell', \omega) + \delta^3 \mathbb{E} [V_{t+1}^{nt}(\ell', \omega') | \omega] \\&= u(\ell, \ell', \omega) + \delta^3 \iint \left\{ \bar{V}_{t+1}^{nt}(\ell', j, \omega') + \mathbb{E} [\varepsilon_j | d^n = j] \right\} dG^n(j | \ell', \omega') dF(\omega' | \omega) \\&= u(\ell, \ell', \omega) + \delta^3 \iint \left\{ \bar{V}_{t+1}^{nt}(\ell', j, \omega') + \gamma \right. \\&\quad \left. + \log \left(\sum_{k=1}^{27} \exp \left(\bar{V}_{t+1}^n(\ell', k, \omega') - \bar{V}_{t+1}^n(\ell', j, \omega') \right) \right) \right\} dG^n(j | \ell', \omega') dF(\omega' | \omega)\end{aligned}$$

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Identification of model primitives

Flow utility parameters: Identification comes from variation in the input of interest and i) where individuals choose to live across their menu of choices and ii) how long they decide to live there

Moving cost parameters: Identification comes from i) comparisons of gross migration rates and ii) how long individuals decide to remain in a particular location

Mass of movers: Identification comes from comparisons of the first-time migration rate to the migration rate of individuals on their second and later moves

Mass of believers: Identification comes from information on where individuals choose to live coupled with variation in rates of warming across **space** and **time**