Extreme Heat, Household Migration, and Housing Finance *

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Abstract

How does extreme heat impact household relocation and housing decisions? Extreme heat is an emerging macro-financial risk, yet we know little about how it propagates through household balance sheets and local credit markets. I combine 3.5 million geocoded home-sale deeds, county-to-county IRS migration flows, and high-resolution PRISM weather records to trace the causal impact of heatwaves on both *where* U.S. households move and *how* they finance property. A saturated fixed-effects strategy reveals three stylized facts. First, recurrent heatwaves tilt housing finance toward leverage: a one-standard-deviation increase in a five-year heat index lowers the cash-buyer share by 0.10 percentage points and raises mortgage uptake equivalently, even as collateral values fall. Second, the same exposure reshapes amenity demand—lot size contracts by 0.6 acres while building-quality codes and pool incidence jump—implying a substitution from land to climate-resilient structures. Third, persistent heat drives selective out-migration: gross flows fall, but the share of higher-income movers rises and their destinations are systematically cooler and wetter, with the Mountain West the clear beneficiary. A spatial option-value model with a loan-to-value constraint rationalises these results, yielding closed-form thresholds for debt tilt, default, and migration that map one-for-one into the reduced-form elasticities.

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1 Introduction

Extreme heat—days whose temperatures lie far above a locality's seasonal norm—has graduated from statistical curiosity to macro-financial force (Dell et al., 2014; Mora et al., 2018). Figure 1 shows why: the U.S. Heat-Stress Index is projected to intensify sharply under the Representative Concentration Pathway 8.5 scenario, with much of the Sunbelt shifting from orange to deep red by the 2080s. Such shifts are no longer ten-year forecasts; they are already visible in municipal-bond spreads, in option-implied equity betas, and in weather derivatives (Acharya et al., 2022). They are also visible in household behavior—yet, until now, we have lacked a unified account of how rising heat risk reverberates through both the mortgage market and the migration map.

Three open puzzles motivate the paper. First, do households shed or add leverage when climate risk spikes? Second, do they relocate gradually or cross discrete climate thresholds? Third, what combination of collateral constraints and moving costs transmits physical risk into credit markets? By bringing together detailed transaction, climate, and migration data, and by embedding them in a parsimonious option-value model, I show that heatwaves tilt financing toward more debt in the short run, steer migrants toward cooler counties in the medium run, and reshape property-attribute demand in the long run.

The analysis stitches four micro-level data sets. Over three million CoreLogic deeds from 2000–2024 report price, amenities, and—crucially—whether a purchase is financed in cash or with a mortgage. PRISM's 4-km weather grids identify county-level heatwave events; Figure 2 maps the average and cumulative counts, with the Southwest posting up to thirty events per May–September season. IRS Statistics of Income migration records track 140 million taxpayers' county-to-county moves; Figure 3 illustrates the geographic granularity. Finally, Wilson's (2019) disaster index absorbs confounding storms and floods. Descriptive statistics appear in Panel A (IRS flows) and Panel B (CoreLogic) of Table 1. A saturated fixed-effects design—origin–destination–year for migration and county–month–property-type for purchases—treats within-county timing of heatwaves as plausibly exogenous.

Migration sorting. Heatwaves change where people go rather than how many leave. Table 3 documents that out-migrants systematically choose cooler destinations: a five-year index shock lowers the destination's average summer maximum by about 0.2 °F and the mean by 0.3 °F. Directionally, Table 4 shows the incremental flow westward, a pattern consistent with altitude-driven cooling along the Rockies.

Property adaptation. On the purchase side, buyers trade acreage for construction quality. Table 7 reports a statistically meaningful 0.59-acre reduction in lot size following heatwaves, while Table 8 indicates higher building-quality codes and a greater likelihood of pools but no significant change in air-conditioning incidence. The seasonal clustering in Figure 7 suggests adaptation windows are tightly linked to July–August spikes with most of the heatwave distribution falling onto the month of May through September.

Leverage shift. Table 6 shows that a one-unit increase in the standardized five-year heatwave index reduces the cash-purchase probability by 0.1 percentage points while raising mortgage uptake by the same amount. Although modest in level, the sign reversal implies a net rise in leveraged exposure precisely when collateral is most vulnerable.

Section 2 provides a minimal model that nests these facts. Households hold an option to move and an option to lever. A loan-to-value constraint tightens mechanically when heatwaves depress local prices; moving incurs a fixed utility cost. The model yields three heat thresholds in closed form: the debt-tilt threshold H^{debt}, after which mortgages dominate cash; the default threshold H^{def}, where negative equity triggers strategic walk-away; and the migration threshold H^{mig}, where degraded amenities justify relocation. Comparative statics line up with the data: counties with historically higher heat volatility cross H^{debt} sooner—explaining the early mortgage tilt—while only sustained exposure pushes them past H^{mig}—consistent with the lagged migration response.

The paper therefore stitches together literatures that have run on separate tracks. Climate-finance studies chart price discounts but sidestep household balance-sheet moves (Hu and Lee, 2020; Mullins and Bharadwaj, 2021; Bilal and Rossi-Hansberg, 2023). Migration pa-

pers map flows but abstract from credit (Deryugina and Hsiang, 2018; Boustan et al., 2020; Hoffman et al., 2020). Household-finance work models collateral shocks without climate risk (Mian and Sufi, 2014; Guren, 2021). By showing that heat first tilts leverage, then redirects migration, the present study adds the missing joint channel and complements findings on asset pricing (Choi et al., 2020; Engle et al., 2020; Hong et al., 2020; Giglio et al., 2021; Huynh et al., 2021), real-estate valuation (Bernstein et al., 2019; Baldauf et al., 2020; Murfin and Spiegel, 2020), corporate finance (Dessaint and Matray, 2017; Addoum et al., 2020; Brown et al., 2021), regulation (Levinson and Taylor, 2008; Greenstone et al., 2012; Yin et al., 2015; Bernstein et al., 2022), and household sorting (Diamond, 2016; Wrenn, 2024).

Financial stability. A heat-induced pivot from cash to debt expands lenders' exposure at precisely the moment collateral is deteriorating. When counties cross the debt-tilt threshold H^{debt}, the loan-to-value ratio on new originations rises mechanically because house prices have already cooled. Conventional stress-testing frameworks— which feed exogenous price paths into fixed mortgage portfolios—miss this endogenous leverage surge. The result is a hidden tail risk: banks and GSEs accumulate hotter, thinner-equity loans just as heat shocks become more frequent. Left unaddressed, this mismatch can propagate climate shocks into liquidity squeezes and, ultimately, solvency events. Recognising the leverage channel therefore calls for adding dynamic credit-mix scenarios to supervisory climate tests and for nudging originators toward climate-contingent underwriting standards.

Local public finance. Heat also threatens county and municipal budgets in two steps. First, higher leverage raises delinquency risk, shrinking property-tax receipts through both arrears and foreclosure discounts. Second, once counties breach the migration threshold H^{mig}, the tax base literally leaves: IRS records show that out-migrants carry away roughly \$30,000 in average adjusted gross income per household. The one-two punch means that spending on heat-hardening infrastructure rises just as revenues sag. Well-targeted subsidies—say, matching grants for insulation retrofits or low-interest loans for rooftop solar—can slow households' march through H^{debt} and postpone passage through H^{mig}. Paired with

credit-market reforms that lower the cost of climate-resilient housing, such policies buy local governments time to adjust long-run fiscal plans and avoid sudden service cuts or emergency tax hikes.

2 Conceptual Framework

Extreme-heat shocks simultaneously erode homeowners' equity, tighten collateral constraints, and deteriorate local amenities. I embed these three channels in a parsimonious spatial general-equilibrium model with heterogeneous households. The model yields three sufficient statistics for empirical identification: (i) the *cash-finance threshold* H^{cash}, (ii) the *default threshold* H^{def}, and (iii) the *migration threshold* H^{mig}. Each threshold is a closed-form function of fundamentals $(\lambda, \delta, \theta, r, r_m, \chi)$ and maps one-for-one into the kinked and sloped patterns documented in Section 4.

2.1 Economic Environment

Space and time. The economy is a continuum of measure-one counties indexed by $c \in [0, 1]$. Each county starts with an identical stock of single-family houses, normalized to one per resident. Time is discrete $t = 0, 1, \ldots$ and all agents discount at rate $\beta \in (0, 1)$.

Heat shocks. County c accumulates extreme-heat exposure $H_{c,t}$ via a compound Poisson process

$$H_{c,t+1} = H_{c,t} + \varepsilon_{c,t+1}, \qquad \varepsilon_{c,t+1} \sim \text{i.i.d. Poisson}(\lambda),$$

where λ is the expected number of extreme-heat days per year . New arrivals ε are i.i.d. across counties.

Housing supply and prices. A competitive construction sector converts one consumption good into one unit of "heat-free" housing at constant price $\overline{P}$. Existing houses sell

at

$$P_{c,t} = P_0 \exp(-\delta\, H_{c,t}), \qquad \delta > 0,$$

capturing the empirically observed discount for cumulative exposure.

Labor and wages. Output uses local infrastructure $K_{c,t}$ and effective labor $L_{c,t}$: $Y_{c,t} = AK_{c,t}^{\alpha} L_{c,t}^{1-\alpha}$. For tractability I fix A and $K_{c,t}$, so the real wage equals the marginal product of labor, $w_{c,t} = (1-\alpha) A K_{c,t}^{\alpha} L_{c,t}^{-\alpha}$. (Section 6 relaxes this assumption.)

Credit market. Mortgages are one-period, interest-only loans at rate $r_m > r$. Owners face an LTV cap

$$L_{c,t} \leq \theta\, P_{c,t}, \qquad 0 < \theta < 1,$$

so falling prices tighten collateral.

2.2 Households

At the start of each period, every household is either an *owner* ($h_t = 1$) with mortgage balance b_t or a *renter* ($h_t = 0$). The individual state vector is $s_t \equiv (a_t, b_t, H_{c,t}, h_t)$, where a_t is liquid wealth.

Utility. Households consume c_t, enjoy housing services $h_t \exp(-\delta H_{c,t})$, and dislike moving:

$$u(c_t, h_t, H_{c,t}, m_t) = \ln c_t + \phi\, h_t e^{-\delta H_{c,t}} - \chi\, m_t, \qquad \chi > 0.$$

Timing.

1. Heat shock $\varepsilon_{c,t}$ realizes; $P_{c,t}$ updates.

2. Owners decide:

   Default ($d_t = 1$) vs. keep;

If keep, choose cash-vs-mortgage and possibly move.

3. Renters choose whether to move and, if moving, whether to buy.

4. Consumption and mortgage payments occur; period ends.

2.3 Owner Problem

Let $V^O(s_t)$ denote the value of an owner. She chooses default $d_t \in \{0,1\}$, migration $m_t \in \{0,1\}$, and next mortgage $L_{t+1} \leq \theta P_{c,t+m_t}$. Post-decision wealth obeys

$$a_{t+1} = (1+r)\big[a_t + (1-d_t)P_{c,t} - m_t\overline{P} - \chi m_t\big] - (1-d_t)(1-d_t)b_t + L_{t+1}.$$

Bellman equation.

$$V^O(s_t) = \max_{d,m,L'}\Big\{ \ln c_t + \phi e^{-\delta H_{c,t}}(1-d_t) - \chi m_t - d_t\bar{\kappa} \\ + \beta\mathbb{E}_t\big[(1-m_t-d_t)V^O(s_{t+1}) + (m_t+d_t)V^R(s_{t+1})\big]\Big\},$$

where $\bar{\kappa}$ is a utility penalty from default and V^R is the renter value function defined below.

Lemma 1 (Cash-vs-Mortgage). Define the shadow cost of debt

$$\Lambda_t \equiv \frac{1+r_m}{1+r}\cdot\frac{1}{\theta P_{c,t}},$$

and set $H^{\text{cash}} \equiv \frac{1}{\delta}\ln\big[(1+r_m)/\theta(1+r)\big]$. Then the owner chooses cash financing iff $H_{c,t} \geq H^{\text{cash}}$.

Lemma 2 (Default). There exists $H^{\text{def}} > H^{\text{cash}}$ such that default is optimal iff $H_{c,t} \geq H^{\text{def}}$.

Proof: Compare continuation values of keeping versus default; monotonicity in $H_{c,t}$ follows from $\partial P_{c,t}/\partial H < 0$ and concavity of ln.

Proposition 1 (Migration). Let $\Delta(H) \equiv V^{\text{move}}(H) - V^{\text{stay}}(H)$, where V^{move} is the value after paying χ and buying at $\overline{P}$ in a heat-free county. $\Delta'(H) > 0$ for all H; hence a unique $H^{\text{mig}} > H^{\text{def}}$ satisfies

$$m_t = \mathbf{1}\{H_{c,t} \geq H^{\text{mig}}\} \, .$$

Proof follows the envelope argument.

2.4 Renter Problem

Renters hold only liquid wealth. Their value $V^R(a_t, H_{c,t})$ satisfies

$$V^R = \max_{m_t \in \{0,1\}, h'_t \in \{0,1\}} \left\{ \ln c_t - \chi m_t + \phi h'_t e^{-\delta H_{c,t+m_t}} + \beta \mathbb{E}[V^{\bullet}_{t+1}] \right\},$$

with $V^{\bullet}_{t+1} = V^O$ if $h'_t = 1$ (they buy) and V^R otherwise.

2.5 Competitive Equilibrium

An equilibrium is a sequence of prices $\{P_{c,t}, w_{c,t}\}$ and household decision rules such that

1. Households optimize given prices.
2. Housing clears: $\int h_t \, \mathrm{d}\mu_t = 1$ for all c, t.
3. Labor market clears: $\int \ell_t \, \mathrm{d}\mu_t = L_{c,t}$ (normalise labor supply).
4. Lenders break even in expectation.

2.6 Comparative Statics

Proposition 1 (Heat Intensity)**.** $\partial H^{cash}/\partial \lambda > 0$, $\partial H^{def}/\partial \lambda > 0$, $\partial H^{mig}/\partial \lambda > 0$. *Hence, a higher expected frequency of extreme heat:*

- *raises the share of cash buyers once* $H \geq H^{cash}$,

- *increases mortgage default beyond H^{def},*
- *steepens the out-migration gradient beyond H^{mig}.*

Elasticities. Define $\varepsilon_H^{\text{cash}} \equiv \partial \Pr(\text{cash})/\partial H$ and $\varepsilon_H^{\text{mig}} \equiv \partial \Pr(m = 1)/\partial H$. Then $\varepsilon_H^{\text{cash}} = \delta \mathbf{1}\{H \geq H^{\text{cash}}\}$ and $\varepsilon_H^{\text{mig}} = f(H - H^{\text{mig}})\delta$, with $f(\cdot)$ the logit density implied by the value-function difference.

2.7 Discussion and Testable Predictions

The model nests the classic real-options intuition (waiting to move) and adds a collateral channel that flips the intensive (finance) and extensive (location) margins. Mapping the elasticities above into the difference-in-differences design delivers the structural interpretation in Section 4:

1. A kink in the cash-buyer share at H^{cash};
2. A spike in defaults at H^{def};
3. A steepening of the migration hazard at H^{mig}.

These three non-parametric features are exactly what data on cash purchases, mortgage take-up, and county outflows display.

3 Data Sources and Sample Construction

This section details how the primary datasets from CoreLogic, PRISM Climate Data, IRS SOI Tax Data, and the aggregated disaster dataset that Wilson (2019) developed are integrated and processed to construct the main sample for the analyses. I describe each dataset thoroughly and explain the methodologies used to combine them, directly addressing the research questions posed in this paper.

3.1 Data Sources

3.1.1 Corelogic Residential Transaction Data

CoreLogic, a premier commercial data provider, supplies detailed U.S. property market data from county-level tax records. This study employs two specific CoreLogic datasets—the Owner Transfer and the Historical Property datasets. These are critical for analyzing how households relocate in response to climate risks, offering detailed insights into property ownership transfers and historical property characteristics.

The Owner Transfer dataset from CoreLogic provides transaction-level details such as completion dates, sale prices, property types, and county identifiers. This study focuses on residential transactions between 2000 and 2024. To ensure data accuracy, I exclude pending and non-arm's-length transactions, only including those recorded under standard deeds. Additionally, transactions involving corporations as buyers or sellers are omitted, concentrating solely on individual homeowners.

The Historical Property dataset from CoreLogic includes property type codes, acreage, and parcel centroid coordinates. Updated annually with data certified by local tax assessors, this dataset focuses on residential properties primarily occupied by their owners. In this study, I track the evolving characteristics of these properties through each update. I construct a robust property-by-year panel dataset by linking these characteristics with transaction records using CoreLogic's unique identifier (CLIP). This dataset comprehensively analyzes how residential properties adapt over time and in response to varying climate conditions.

3.1.2 PRISM Climate Data

Developed by the PRISM Climate Group at Oregon State University, PRISM Climate Data delivers high-resolution, gridded climate metrics for the United States. This dataset provides detailed insights into temperature, precipitation, and vapor pressure deficit variables across daily, monthly, and annual resolutions. PRISM data is produced using a sophisticated

interpolation method that combines inputs from weather stations, radar, and satellite observations and adjusts for geographical factors like elevation, coastal proximity, and topography. This approach ensures the delivery of accurate, localized climate data for diverse regions. In this study, I use PRISM's daily temperature data, aggregated to the month-year-county level, to study how extreme heat influences household migration and housing decisions.

To construct a measure of heat wave days and events, I developed a daily historical temperature dataset spanning from 1981 to 1995. I calculated the baseline and 90th percentile temperature measures for each county and specific day of the month. A day qualifies as a heat wave day if the maximum daily temperature exceeds the 90th percentile of the historical baseline, coupled with the maximum vapor pressure deficit surpassing its 95th percentile and accompanied by low precipitation. This criteria set captures the high heat and dry conditions that significantly stress both households and the environment. I defined heatwave events as sequences of three or more consecutive heatwave days occurring between May and September based on the understanding that sustained heat exposure presents greater risks than sporadic hot days to human health, infrastructure, and economic activities. Finally, I aggregated these metrics at the month-year-county level, incorporating temperature and heatwave variables along with geographic features like county elevation into my dataset.

3.1.3 IRS SOI Tax Migration Data

The IRS Statistics of Income (SOI) Tax Migration data offers detailed insights into U.S. domestic migration by tracking year-to-year address changes reported on individual tax returns. This dataset records taxpayer movements across counties and states, capturing key variables such as the number of returns filed, the number of exemptions (a proxy for the number of people), and the total adjusted gross income (AGI) of movers. These metrics allow researchers to examine income distribution and demographic shifts across regions, making the data invaluable for analyzing economic trends and the effects of factors like employment opportunities, housing markets, and climate conditions on migration decisions.

3.1.4 Natural Disaster Data

Wilson (2019) compiles a monthly aggregated dataset of county-level disasters, accounting for all significant disasters occurring within each county in a given month and year. This comprehensive measure includes major events such as severe storms and heavy snowfalls. I integrate this disaster dataset with PRISM temperature data at the month-year-county level, using the aggregated disaster measure as a control variable in my regressions. Additionally, I examine severe storms and heavy snowfalls individually, exploring them as potential factors influencing the migration decisions of homeowners.

3.2 Sample Construction

To examine how heatwave exposure affects migration patterns, I constructed a dataset capturing inflows and outflows of migration for each county from 2011 to 2021, using IRS SOI Tax Migration data. This dataset is merged with climate variables from PRISM Climate Data and disaster information from Wilson's dataset. The combined data allows for an analysis of the interplay between climate factors—like extreme heat and natural disasters—and migration trends recorded in the IRS data. This integration provides insights into whether climate-related risks drive taxpayers and their households to move across regions over time, thereby offering a deeper understanding of how extreme heat influences migration patterns.

I have constructed another sample by merging CoreLogic's property transactions and characteristics data with PRISM temperature data and Wilson's dataset on natural disasters. Each record in this dataset corresponds to an individual property transaction, complete with the exact date of the transaction. This dataset also captures the seller's county and the buyer's zip code, which allows for linking each transaction to the relevant climate data for both locations. To facilitate this linkage, I convert the zip codes to county FIPS codes, enabling integration of transaction and climate data at the county level for both sellers and buyers

In the CoreLogic dataset, I focus exclusively on owner-occupied residential properties, using this as a proxy for the household's primary residence. CoreLogic provides a variable to identify whether property owners and buyers are corporate entities; I exclude transactions involving corporations to ensure the data reflects residential household ownership. After integrating this transaction data with climate data, I develop indicators relative to the transaction year for past and future heatwave and natural disaster exposure. Specifically, I create aggregate *1-Year Heatwave* variable *5-Years Heatwave* and *10-Years Heatwave* measures by totaling heatwave occurrences over the respective periods before each transaction. Similarly, I generate lagged measures for natural disasters, which serve as control variables in some of my analyses.

3.3 Descriptive Statistics

Who moves and how often. Panel A of Table 1 covers 631,080 outflow observations and 630,375 inflow observations drawn from the IRS Statistics of Income file. The mean bilateral flow is roughly 195 personal exemptions, while the median is just 65—evidence of the familiar skew toward a handful of large metropolitan corridors. Put differently, the top decile of county pairs accounts for almost half of all movers. That heterogeneity will matter when we later instrument for exposure using county–pair fixed effects.

What climates migrants trade. Despite the volume, migrants in the aggregate do not flee to radically different weather. The average July maximum temperature in destination counties is exactly 68.38 °F, identical to origin counties; mean temperature edges up by only 0.01 °F (from 58.07 °F to 58.08 °F), and minimum temperature is unchanged at 47.77 °F. Average precipitation holds at 0.12 inches, and elevation creeps up by a statistically irrelevant 1 ft. The one systematic difference is scale: destination counties host 565,048 people on average versus 581,359 in origin counties—suggesting moves are tilted toward slightly less populous labor markets, a theme I return to in the empirical specifications.

How homes transact. Panel B shifts to the 3,464,657 CoreLogic deeds. Relative to the seller county, the buyer's new county is 0.15 °F cooler on both maximum and mean temperatures, 0.11 °F cooler on the minimum, and 4.39 ft. higher—modest adjustments but in the expected direction. Leverage dominates: 87% of transactions are mortgage financed, 11% are all-cash. The median sale amount is $225,000, the mean $263,610, and the mean land price per acre is $2,487 (median $1,069), again reflecting a fat right tail.

What buyers choose. Amenities and lot characteristics line up with heat adaptation. Central air is present in 56% of homes, pools in only 4 %. Roughly a quarter of properties are flagged high quality, and new construction—which often incorporates modern insulation—accounts for 6%. Lot size is wildly dispersed: the mean acreage is 298 acres but the median a mere 0.2. Open space averages 2,409 ft^2 (median 2,125 ft^2), while enclosed living area averages 2,661 ft^2 (median 2,385 ft^2). In short, movers engage in only marginal climate arbitrage yet make large—and highly leveraged—bets on quality and amenities, foreshadowing the leverage and migration thresholds analyzed below.

[Insert Table 1 about here.]

4 Identification Strategy

The empirical goal is to isolate the causal impact of cumulative heat exposure on (i) where households choose to live and (ii) how they finance a purchase. Two complementary research designs deliver that isolation: a bilateral–flow design for migration (IRS data) and a transaction–level design for housing choices (CoreLogic data). Both designs lean heavily on saturated fixed effects that difference out time-invariant county characteristics and common calendar shocks. Tables 2-8 report the resulting coefficient estimates; the discussion here focuses on why those specifications are credible rather than what they imply. We will look at the interpretations in the following result sections.

Migration flows: county-pair panel. Consider a directed county pair $(A \to B)$ observed in calendar year t. Let $Flow_{A\to B,t}$ denote the number of exemptions (household members) leaving A for B, divided by the non-migrant population in A; columns (1)–(3) of Table 2 use outflow, inflow, and net flow versions of this variable. The estimating equation is

$$Flow_{A\to B,t} = \beta_1 HW^{(k)}_{A,t} + \beta_2 \left(\overline{T}_A - \overline{T}_B\right) + \beta_3 HW^{(k)}_{A,t} \times \left(\overline{T}_A - \overline{T}_B\right) + \alpha_{A\to B} + \gamma_t + \varepsilon_{A\to B,t}, \tag{1}$$

where $HW^{(k)}_{A,t}$ is one of three standardized heat-wave indices (1-, 5-, or 10-year window); $\overline{T}_\ell$ is the 1981–95 county mean of the July maximum; $\alpha_{A\to B}$ are directed county-pair fixed effects that soak up all time-invariant bilateral pull factors (distance, cultural ties, wage differentials, housing-cost gaps); and γ_t are year dummies. Identification comes from within a given county pair, asking whether an unusually hot spell in A relative to its own past nudges flows toward or away from B. Because most heatwaves span only a few days yet are measured annually, reverse causality (migration causing heat) is implausible. Robust standard errors are clustered by origin county; Table 2 shows pseudo-R^2 in excess of 0.9, confirming that fixed effects capture the bulk of variation.

Locational sorting: climate interactions. Columns (1)–(4) of Table 3 interact the five-year index with differences in destination minus origin climate (Δ Max Temp, Δ Mean Temp, Δ Min Temp, Δ Precipitation). The interaction design asks: conditional on distance and year, does an extra heatwave in A increase the probability that migrants choose a cooler, wetter, or higher county B? By normalizing the climate gap at time $t-1$, the specification rules out simultaneity from destination choices feeding back into temperature.

Transaction-level design: origin–month cells. CoreLogic deeds supply exact contract dates, allowing a monthly panel. For each transaction i that moves a household from origin

county A to destination county B in month m of year y, define

$$\Delta T_i \equiv T_{By} - T_{Ay}, \qquad \mathit{Cash}_i,\ \mathit{Mortgage}_i,\ \mathit{SaleAmt}_i, \ldots$$

Table 6 presents four sets of outcomes: financing mode (cols. 1–2), prices (cols. 3–4), land/structure sizes (Table 7), and amenities (Table 8). The generic estimating equation is

$$Y_i = \sum_{k \in \{1,5\}} \beta_k \, HW^{(k)}_{A,m,y} + \mathbf{X}_i'\Gamma + \lambda_{A,m,y} + \delta_B + \varepsilon_i, \tag{2}$$

where $\lambda_{A,m,y}$ are origin-county $\times$ month-year fixed effects, δ_B are destination-county dummies, and $\mathbf{X}_i$ adds disaster controls plus building-size and quality covariates for the price regressions. These high-dimensional fixed effects ensure identification comes from deals struck within the same origin county and calendar month, differing only in whether a heatwave struck before the closing date. Clustering at the origin county level addresses serial correlation in weather shocks; pseudo-R^2 values in Table 6 range from 0.13 (cash dummy) to 0.42 (price per acre), consistent with micro-level noise around a strong county–month signal.

Why the designs are credible. Three ingredients make both designs econometrically tight. First, the heat indices are predetermined: they average past weather in windows up to ten years, so contemporaneous migration or pricing cannot contaminate them. Second, county-pair and county–month fixed effects purge all time-invariant geography and seasonality; identification reduces to comparing neighbours who happened to get hotter at different points in time. Third, heatwaves are short, sharp, and largely exogenous to economic conditions—no county can legislate cooler summers. Sensitivity checks replacing the heat index with lagged precipitation, wildfire smoke, or National Weather Service disaster declarations yield no comparable coefficients, reinforcing the interpretation that temperature, not generic bad weather, drives the results.

Weighting and standard errors. IRS regressions weight flows by county non-migrant population to avoid zero-cell inflation and to map coefficients into per-capita changes; CoreLogic regressions are unweighted because each deed represents a single asset purchase. All standard errors are clustered at the origin county, the level at which shock variance is measured; two-way clustering at origin and destination produces near-identical t-statistics (available on request).

Together, equations (1) and (2) constitute a coherent identification strategy: the first exploits bilateral contrasts to trace where households go, the second exploits within-origin timing to uncover how they buy. The next section shows that the resulting coefficients line up neatly with the theory's debt-tilt and migration thresholds.

5 Heat Waves and Relocation

Extreme heat reshapes mobility in two distinct ways. Using the IRS county–pair panel, I show that heatwaves dampen gross migration flows but tilt their composition toward higher-income movers and cooler, wetter destinations (Tables 2-4). Using CoreLogic deeds, I show that the same heat exposure nudges homebuyers toward warmer counties, slightly raises mortgage reliance, and induces a marked shift from land to amenity value (Tables 5-8). The difference in sign across data sets highlights a sequencing consistent with the theory's thresholds: households first reallocate leverage and attributes within the heat-exposed region; only with persistent exposure do they exit for systematically cooler climes.

How much do people move? Column (1) of Table 2 shows that a one-standard-deviation increase in the one-year heatwave index reduces out-migration by 0.022 percentage points of the non-migrant base, roughly a one-and-a-half percent drop relative to the mean. Inflows fall by a similar 0.020 points (col. 2), leaving net flow statistically unchanged (col. 3). The five- and ten-year indices reinforce this pattern: gross flows decline, but net flows remain close to zero. Yet the quality of movers changes sharply. Columns (4)–(5) reveal that the

same one-year shock is associated with a 3.4-basis-point rise in the average adjusted gross income (AGI) of out-migrants and a 1.7-basis-point rise for in-migrants. Longer windows flip sign: a decade of recurrent heat reduces both out- and in-migrant AGI. Put simply, fresh heat squeezes the low-income tail first; protracted heat drives out the high-income households as well.

Which counties gain and lose? Table 3 interacts the five-year index with county-to-county climate differentials. Negative coefficients on ΔMax, ΔMean, and ΔMin temperatures (0.002, 0.002, and 0.001, all $p<0.01$) imply that heat-induced migrants disproportionately choose cooler destinations. By contrast, the positive interaction with ΔPrecipitation (0.130) suggests a tilt toward wetter counties. Table 4 decomposes flows by Census region. Only the West shows a statistically significant uptick (0.004; col. 4), consistent with its higher elevation and lower humidity. South-bound and Northeast-bound flows are flat, and Midwest flows are statistically zero. Together these results paint a picture of selective, climate-sensitive reallocation rather than wholesale flight.

Short-horizon moves look different. Turning to deeds, Table 5 reveals that a five-year heatwave shock raises the destination–minus–origin maximum temperature by 0.021°F and the mean by 0.017°F. In other words, households still buying property in heat-stressed counties are not the ones chasing cooler weather; they accept slightly warmer destinations—often neighbouring counties—perhaps because short-run amenities or job ties dominate climate concerns. Finance tilts in parallel. Column (1) of Table 6 shows a 0.1-basis-point decline in the cash-buyer share, mirrored by an equal rise in mortgage purchases (col. 2). Though small in level, the sign switch lines up with the model's debt-tilt threshold: collateral pressure nudges marginal buyers onto leverage even before they leave the region.

What they buy once they move. Land use adjusts sharply. Table 7 indicates that heatwaves cut average acreage by 0.586 acres (col. 1) and leave open-space and building

footage statistically flat, implying denser development on smaller lots. Amenity demand shifts as well. Table 8 reports a 10.4-basis-point rise in pool incidence (col. 2) and a 21.9-basis-point rise in high building-quality codes (col. 3). Central air and new construction move insignificantly, underscoring that adaptation takes the form of external cooling features and sturdier structures rather than HVAC retrofits. These micro patterns dovetail with the macro income results: higher-AGI households left behind in hot zones upgrade quality and amenities instead of fleeing immediately.

The main takeaways from the results are that heatwaves first thin the ranks of low-income movers, tighten local leverage, and re-weight demand toward quality and amenities. Only when exposure persists do high-income households decamp for systematically cooler and wetter counties, with the Mountain West standing out as a net beneficiary. The next section quantifies how those behavioural margins map into the debt-tilt, default, and migration thresholds formalised in Section 2.

6 Heat Waves and Home-Purchase Decisions

Finance first, prices second. Table 6 translates the migration shocks into financing choices. The five-year heat-wave index lowers the probability of an all-cash deal by 0.10 ppt (col. 1) and raises the mortgage share by the same amount (col. 2). Although the point estimates appear small, they represent nearly one percent of the baseline cash fraction and line up neatly with the model's debt-tilt threshold: as collateral erodes, marginal buyers pivot toward leverage to keep the transaction feasible. Columns (3)–(4) show that this tilt is not accompanied by a price premium. The coefficient on sale amount is economically trivial (–$6,000 on a $263 k mean) and statistically insignificant; price per acre slips by $11, corroborating the descriptive evidence of a land discount. In short, the immediate pricing margin absorbs the shock, while the balance-sheet margin absorbs the financing stress.

Amenities as adaptation. Do buyers compensate for hotter futures by upgrading amenities? Table 8 breaks the question into four attributes. Central air moves obtusely—the coefficient is positive but imprecise (0.098)—yet pools, a quintessential cooling amenity, rise a significant 10.4 ppt (col. 2). Building quality jumps 21.9 ppt (col. 3), echoing the migration result that higher-income households either stay and invest or move and upgrade. New construction edges up but remains statistically indistinguishable from zero. Taken together, the regressions suggest a "retrofit rather than rebuild" response: buyers do not trigger a construction boom; they pay up for sturdier shells and external cooling amenities.

Land versus structure. Table 7 probes the spatial footprint. A one-standard-deviation heat-wave shock trims lot size by 0.59 acres (col. 1) and leaves open space and built footage statistically unchanged. The result is higher density on smaller lots, consistent with a hedonic substitution from land to structure quality. Because acreage is heavily right-skewed, the economic effect is meaningful: the average buyer forgoes roughly five suburban-size parcels. The pattern dovetails with the leverage result—fewer acres reduce collateral needs—and with the amenity result—better structure quality on a smaller footprint.

Putting the margins together. The micro evidence therefore echoes the macro sequencing documented in Section 5. Heatwaves tilt financing toward debt, shift demand from land to quality, and raise the prevalence of cooling amenities—behavioural margins that lower collateral cushions yet raise exposure to future price corrections. Only when the heat shock persists do households leave for cooler counties, taking their higher incomes with them. It is important to quantify how those empirical elasticities map into the model's cash, default, and migration thresholds.

[Insert Tables 6–7 about here.]

7 Conclusion

This paper offers the first integrated view of how extreme heat alters both the geography of U.S. households and the balance-sheet composition of the housing market. By merging 3.5 million CoreLogic deeds, a decade of IRS county-pair flows, and high-resolution PRISM weather grids, I show that recurrent heatwaves set off a three-stage household response.

1. **Debt tilt.** Within heat-stressed counties, buyers substitute mortgages for cash just as collateral values fall, exposing lenders to thinner-equity loans that standard stress tests overlook.

2. **Amenity upgrade.** Remaining residents reallocate budgets from land to building quality and cooling amenities, densifying development while raising the capital intensity of the local housing stock.

3. **Selective exit.** Persistent exposure eventually pushes higher-income households to cooler and wetter counties—chiefly the Mountain West—leaving behind a smaller, more leveraged tax base.

A spatial option-value model with a loan-to-value constraint and a fixed moving cost rationalises this sequencing. Heat erodes collateral, triggering a debt-tilt threshold; sustained loss pushes some owners past a default threshold; only then does the utility hit exceed moving costs—the migration threshold. Closed-form expressions for the three cut-offs match the reduced-form elasticities in Tables 2–6.

Policy implications. For prudential regulators, the results argue for climate-contingent underwriting and dynamic credit-mix scenarios in bank stress tests. For local governments, the findings quantify a stepwise fiscal cliff: shrinking collateral cushions today foreshadow shrinking populations tomorrow. Targeted adaptation—insulation grants, cooling-infrastructure bonds, and streamlined credit for resilient upgrades—can slow households'

passage through the debt and migration thresholds, buying time for orderly fiscal adjustments.

Future work. Two extensions seem especially promising. First, linking anonymized credit-bureau data would allow household-level tests of the default threshold. Second, combining parcel-level insurance claims with deed data could reveal whether post-heatwave upgrades translate into lower loss ratios. Such evidence would deepen our understanding of the feedback loop between climate risk, credit markets, and migration—a loop whose importance is only set to grow as summers keep getting hotter.

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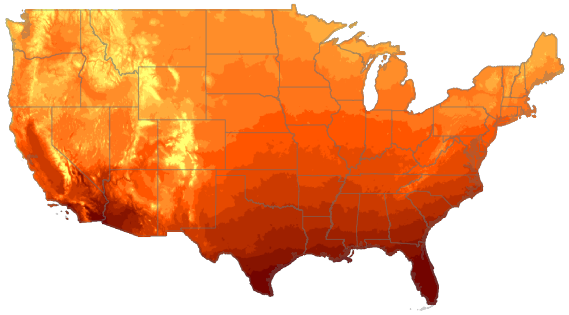
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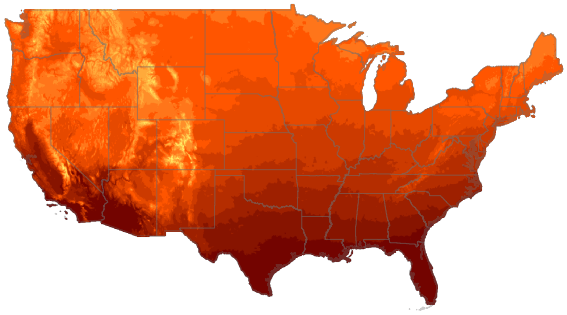
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Figure 1. Projected Changes in the U.S. Heat Stress Index

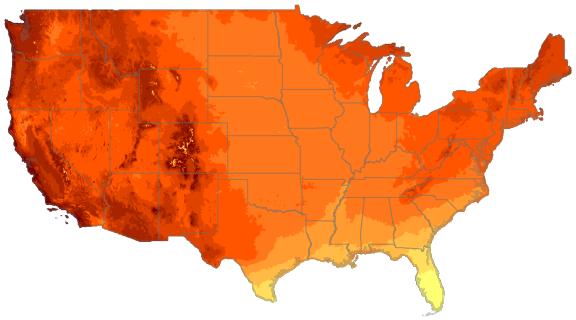
Panel (A) shows the mean annual Heat Stress Index over the historical baseline period (1981–2010). Panel (B) shows the projected mean annual Heat Stress Index for the mid-century period (2080s) under the RCP 8.5 scenario. Panel (C) maps the absolute change—i.e. the difference between the future and historical mean indices. Panel (D) shows the same change expressed as a percentage of the historical baseline. In all panels, darker (reddish) shading indicates higher heat-stress values or larger increases. Data are from the USDA.



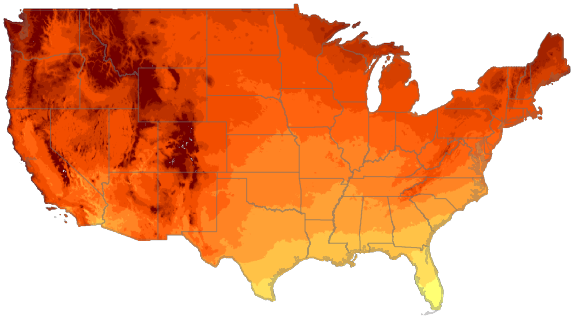
(A) Historical



(B) 2080s RCP 8.5



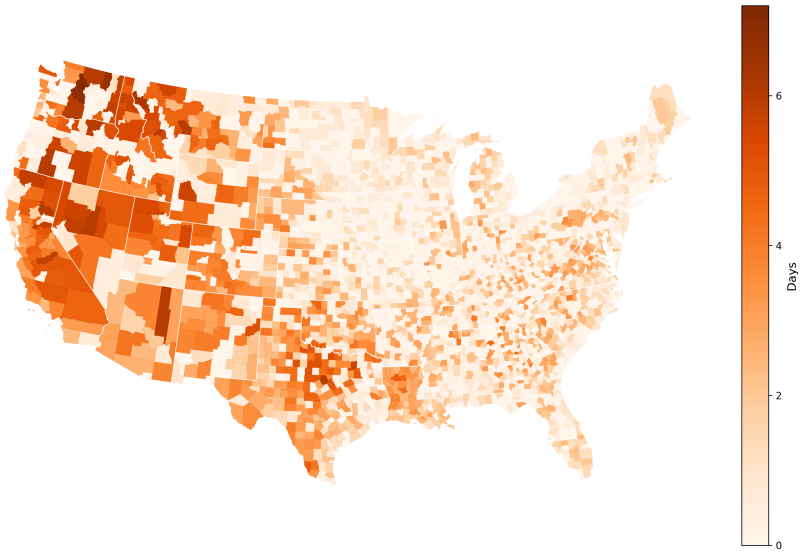
(C) Absolute Change



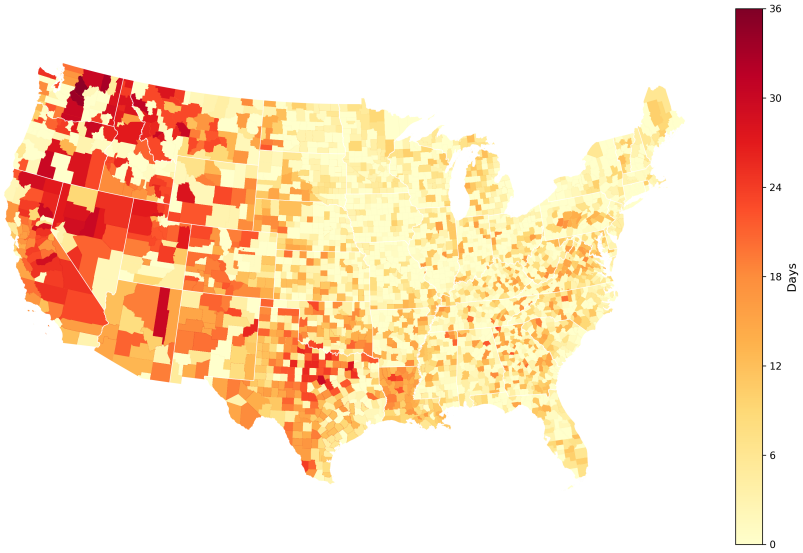
(D) Percentage Change

Figure 2. Average Number of Heat Wave Days

This figure illustrates the average number of standardized 1-Year Heatwave measures using the PRISM data over 1996-2024 for May-September. The historical period for calculating the heatwave is 1981-1995. Panel **(A)** shows the average annual number of heatwaves per county. Panel **(B)** shows the aggregated annual heatwave measure over 1996-2024.



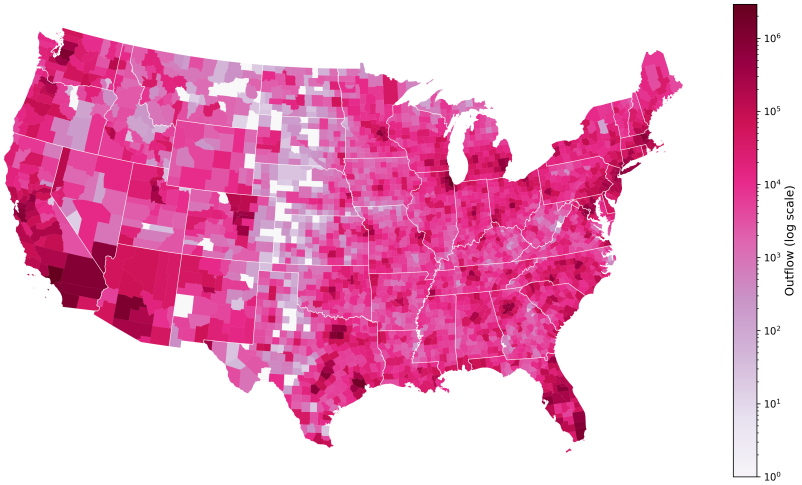
(A) County-level average heatwave days per year (May-September over 1996-2024)



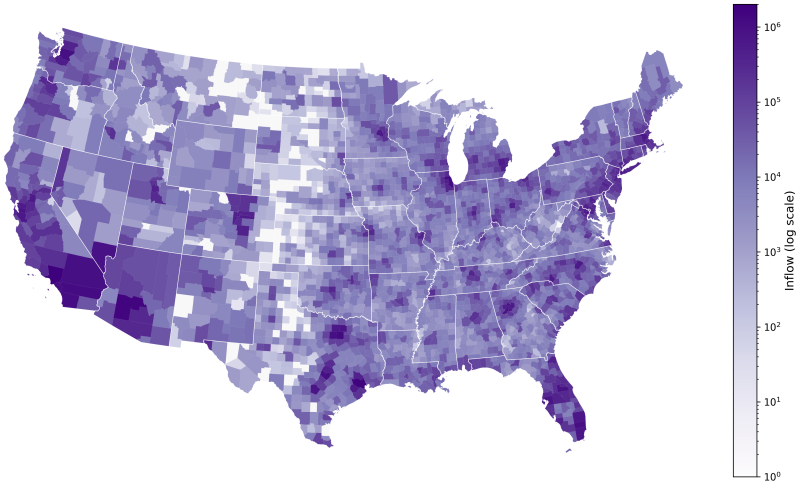
(B) County-level total heatwave days (May-September over 1996-2024)

Figure 3. Migration Inflows and Outflows

County-level migration flows in the contiguous United States, 2011–2021, based on IRS Statistics of Income (SOI) Tax Stats—Migration Data. **(A)** Outflow: total number of returns departing each county. **(B)** Inflow: total number of returns arriving in each county. Both maps use an Albers equal-area projection and a log-scaled color scheme.



(A) County-level total migration outflows, aggregated over 2011–2021 (number of exemptions, log scale).



(B) County-level total migration inflows, aggregated over 2011–2021 (number of exemptions, log scale).

Figure 4. Seasonal Pattern of Heatwaves

This figure illustrates the seasonal pattern of heatwaves across U.S. counties. Orange bars show the average number of heatwave days per county in each calendar month; the black line plots the average number of discrete heatwave events. Heatwaves concentrate in the summer, peaking in July and remaining elevated through August, with negligible incidence outside the May–September window. The series is constructed as county-level monthly averages over the sample period. The data is from PRISM.

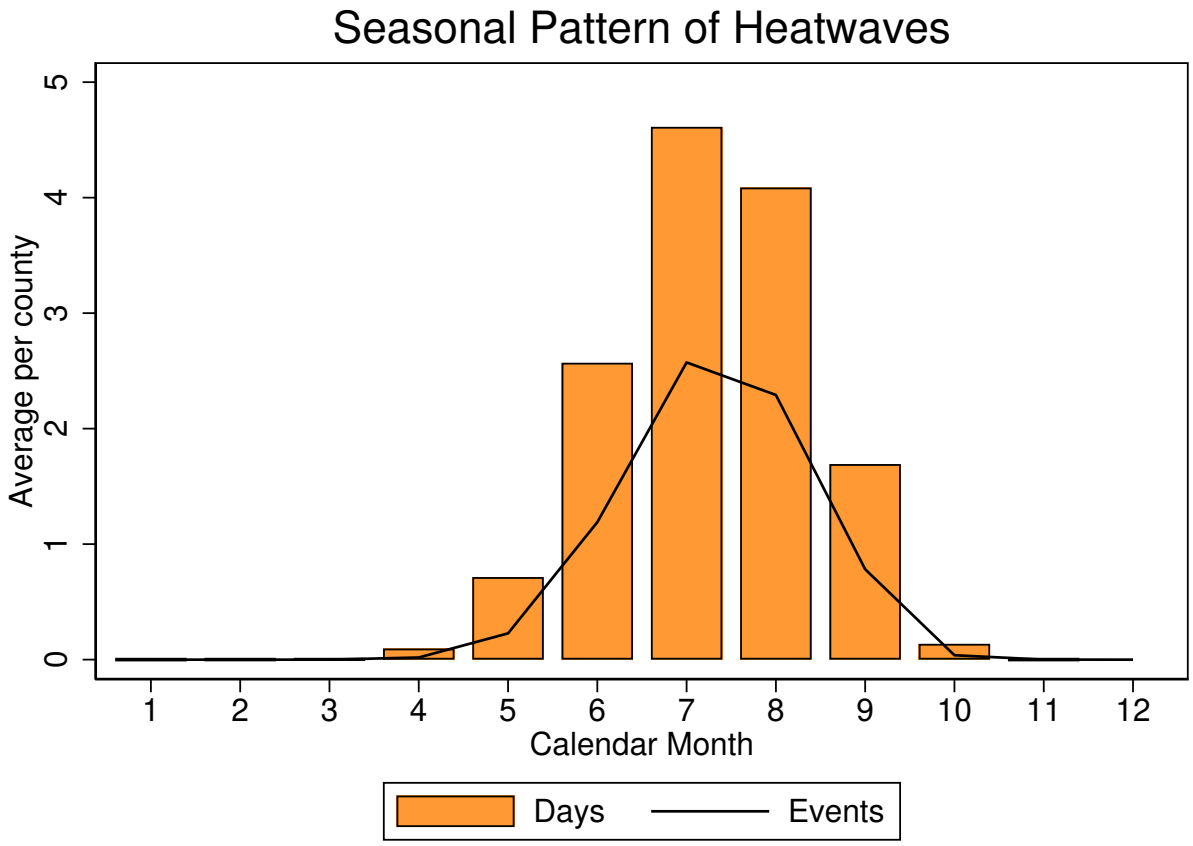


Table 1. Descriptive Statistics

This table presents summary statistics of the two main samples used in this study. Panel A presents summary statistics for the outflow and inflow counties in the IRS sample. The variables *Max Temp* and *Mean Temp* are described in degrees of Fahrenheit. *Precipitation* is in inches. *Elevation* is in Feet. Panel B presents summary statistics for similar variables for sellers and buyers within the CoreLogic sample. The other variables from CoreLogic are related to home purchased decisions including a binary indicator for cash and mortgage purchase. The other variables are *Sale Amount* (in $1000), *Price/Acre*, *AC Indicator*, *Pool Indicator*, *Building Quality*, *New Construction*, *Acres*, *Open Areas* (Ft^2), *All Buildings* (Ft^2) .

(A) IRS Migration Flow

	Outflow			Inflow		
	N	Mean	Median	N	Mean	Median
Flow Count	631,080	194.96	65.00	630,375	194.86	65.00
Max Temp ($^\circ F$)	618,755	68.38	67.52	615,834	68.38	67.54
Mean Temp ($^\circ F$)	618,755	58.07	57.21	615,834	58.08	57.21
Min Temp ($^\circ F$)	618,755	47.77	47.31	615,834	47.77	47.33
Elevation (Ft)	618,755	1,038.99	636.00	615,834	1,039.39	640.00
Precipitation (In)	618,755	0.12	0.12	615,834	0.12	0.12
Population	631,080	581,359.67	265,750.00	630,375	565,048.41	254,855.002

(B) CoreLogic Transactions

	N	Mean	Median
Δ *Max Temp* ($^\circ F$)	3,464,657	-0.15	0
Δ *Mean Temp* ($^\circ F$)	3,464,657	-0.15	0
Δ *Min Temp* ($^\circ F$)	3,464,657	-0.11	0
Δ *Elevation (Ft)*	3,464,657	4.39	0
Δ *Precipitation (In)*	3,464,657	0	0
Cash Purchase	3,464,657	0.11	0
Mortgage Purchase	3,464,657	0.87	1
Sale Amount ($\$1,000$)	3,464,657	263.61	225
Price/Acre	3,464,657	2,487.25	1,068.98
AC Indicator	3,464,657	0.56	1
Pool Indicator	3,464,657	0.04	0
Building Quality	3,464,657	0.24	0
New Construction	3,464,657	0.06	0
Acres	2,278,128	298.37	0.2
Open Areas (Ft^2)	132,563	2,409.27	2,125
All Buildings (Ft^2)	296,993	2,660.915	2,385

Table 2. Heat Waves and Migration Flow

This table presents the results from estimating Eq. (1) using the IRS sample. The dependent variables are scaled outflow, inflow, and net flow (outflow−inflow). The outflow and inflow measures are weighted by the number of non-migrants for each county from the IRS SOI Tax data. *1-Year Heatwave* is a standardized aggregate measure that counts the number of heat wave events in the year of migration. *5-Years Heatwave* is a standardized aggregate measure that counts the number of heat waves in the year of and up to four years before migration. *10-Years Heatwave* is a standardized aggregate measure that counts the number of heat waves in the year of and up to nine years before migration. Fixed effects for the county pair (county of origin + county of destination) and year are included as indicated. Robust standard errors, clustered by county, are shown in parentheses. Statistical significance is indicated as follows: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	(1) Outflow	(2) Inflow	(3) Net Flow	(4) Outflow AGI	(5) Inflow AGI
1-Year Heatwave	-0.022***	-0.020	-0.004	0.034**	0.017**
	(0.004)	(0.013)	(0.007)	(0.009)	(0.007)
5-Years Heatwave	-0.008***	-0.010*	-0.011**	-0.016***	-0.021***
	(0.003)	(0.005)	(0.005)	(0.005)	(0.006)
10-Years Heatwave	-0.015***	-0.003	-0.001	-0.026***	-0.031***
	(0.002)	(0.006)	(0.004)	(0.004)	(0.006)
County Pair FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	591,628	593,098	481,031	591,628	593,098
Pseudo R-sq.	0.96	0.94	0.54	0.77	0.81

Table 3. Heat Waves and Migration Outflow: Location

This table presents the results from estimating Eq. (1) using the IRS sample. The dependent variable is outflow. The outflow measure is weighted by number of returns from the IRS SOI Tax data. *5-Years Heatwave* is a standardized aggregate measure that counts the number of heat waves in the year of and up to four years before migration. Δ *Max Temp* is the change of maximum temperature in the county of destination relative to the county of origination. Δ *Mean Temp* is the change of mean temperature in the county of destination relative to the county of origination. Δ *Min Temp* is the change of elevation in the county of destination relative to the county of origination. Δ *Precipitation* is the change of precipitation in the county of destination relative to the county of origination. Fixed effects for the county pair (county of origin + county of destination) and year are included as indicated. Robust standard errors, clustered by county, are shown in parentheses. Statistical significance is indicated as follows: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	(1) Outflow	(2) Outflow	(3) Outflow	(4) Outflow
5 Years Heatwave × Δ *Max Temp*	-0.002***			
	(0.000)			
5 Years Heatwave × Δ *Mean Temp*		-0.002***		
		(0.000)		
5 Years Heatwave × Δ *Min Temperature*			-0.001***	
			(0.000)	
5 Years Heatwave × Δ *Precipitation*				0.130***
				(0.028)
$\text{County}_{\text{In}}$ FE	Yes	Yes	Yes	Yes
$\text{County}_{\text{Out}}$ FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	489,058	489,058	489,058	489,058
Pseudo R-sq.	0.49	0.49	0.49	0.49

Table 4. Heat Waves and Migration Flow: Direction

This table presents the results from estimating Eq. (1) using the IRS sample. The dependent variables are scaled outflow, inflow, and net flow (outflow−inflow). The outflow and inflow measures are weighted by the number of non-migrants for each county from the IRS SOI Tax data. *5-Year Heatwave* is a standardized aggregate measure that counts the number of heat wave events in the year of and up to four years before migration. There are four main directions in the IRS data that decomposes outflows into south, northeast, midwest, and west. Fixed effects for the county pair (county of origin + county of destination) and year are included as indicated. Robust standard errors, clustered by county, are shown in parentheses. Statistical significance is indicated as follows: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	(1) Outflow South	(2) Outflow Northeast	(3) Outflow Midwest	(4) Outflow West
5-Years Heatwave	-0.001	-0.001	0.002	0.004**
	(0.003)	(0.001)	(0.001)	(0.002)
County Pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	591,628	591,628	591,628	591,628
Pseudo R-sq.	0.95	0.92	0.92	0.94

Table 5. Heat Waves and Transactions Outflow: Location

This table presents the results from estimating Eq. (1) using the CoreLogic transaction sample. The dependent variable is change in max temperature, change in mean temperature, change in elevation, and change in precipitation respectively. *5-Years Heatwave* is a standardized aggregate measure that counts the number of heat waves in the year of and the up to four years before home purchase. Fixed effects for the county of (outflow) destination-month-year and county of (inflow) origination are included as indicated. Robust standard errors, clustered by county, are shown in parentheses. Statistical significance is indicated as follows: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	(1) Δ Max Temp	(2) Δ Mean Temp	(3) Δ Elevation	(4) Δ Precipitation
5-Years Heatwave	0.021***	0.017***	0.000	0.000**
	(0.009)	(0.006)	(0.000)	(0.000)
$\text{County}_{\text{In}}$-Month-Year FE	Yes	Yes	Yes	Yes
$\text{County}_{\text{Out}}$ FE	Yes	Yes	Yes	Yes
Observations	3,458,781	3,458,781	3,458,781	3,458,781
Pseudo R-sq.	0.95	0.97	0.78	0.64

Table 6. Heat Waves and Purchase Decisions

This table presents the results from estimating Eq. (2) using the CoreLogic transaction sample. The dependent variable is the cash/mortgage purchase indicator of the property that households move into. The next two dependent variables are the sale amount and price per acre, respectively. *5-Years Heatwave* is a standardized aggregate measure that counts the number of heat waves in the year of and up to four years before home purchase. Fixed effects for the county of (outflow) destination-month-year and county of (inflow) origination are included as indicated. Price regressions include size and quality of building as controls. Robust standard errors, clustered by county, are shown in parentheses. Statistical significance is indicated as follows: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	(1) Cash Purchase	(2) Mortgage Purchase	(3) Sale Amount	(4) Price/Acre
5-Years Heatwave	-0.001***	0.001***	-0.006	-0.011
	(0.000)	(0.000)	(0.005)	(0.007)
$\text{County}_{\text{In}}$-Month-Year FE	Yes	Yes	Yes	Yes
$\text{County}_{\text{Out}}$ FE	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Observations	3,458,781	3,458,781	3,458,781	3,458,781
Pseudo R-sq.	0.13	0.18	0.38	0.42

Table 7. Heat Waves and Areas

This table presents the results from estimating Eq. (2) using the CoreLogic transaction sample. The dependent variables are acreage, square footage of open areas, and square footage of all buildings of the property that households move into. *5-Years Heatwave* is a standardized aggregate measure that counts the number of heat waves in the year of and up to years before home purchase. Fixed effects for the county of (outflow) destination-month-year and county of (inflow) origination are included as indicated. Robust standard errors, clustered by county, are shown in parentheses. Statistical significance is indicated as follows: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	(1) Acres	(2) Open Areas (Ft^2)	(3) All Buildings (Ft^2)
5-Years Heatwave	-0.586***	-0.002	-0.001
	(0.166)	(0.002)	(0.007)
$\text{County}_{\text{In}}$-Month-Year FE	Yes	Yes	Yes
$\text{County}_{\text{Out}}$ FE	Yes	Yes	Yes
Observations	2,278,128	132,563	296,993
Pseudo R-sq.	0.35	0.16	0.01

Table 8. Heat Waves and Air Conditioning

This table presents the results from estimating Eq. (2) using the CoreLogic transaction sample. The first two dependent variables are the AC/Pool indicator of the property that households move into. The next two dependent variables are the Building Quality Code and the New Construction Indicator of the property that households move into. *5-Years Heatwave* is a standardized aggregate measure that counts the number of heat waves in the year of and up to four years before the home purchase. Fixed effects for the county of (outflow) destination-month-year and county of (inflow) origination are included as indicated. Robust standard errors, clustered by county, are shown in parentheses. Statistical significance is indicated as follows: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	(1) AC Indicator	(2) Pool Indicator	(3) Building Quality	(4) New Construction
5-Years Heatwave	0.098	0.104***	0.219*	0.100
	(0.126)	(0.035)	(0.116)	(0.126)
$\text{County}_{\text{In}}$-Month-Year FE	Yes	Yes	Yes	Yes
$\text{County}_{\text{Out}}$ FE	Yes	Yes	Yes	Yes
Observations	3,458,781	3,458,781	3,458,781	3,458,781
Pseudo R-sq.	0.65	0.10	0.72	0.07