Interactive, County-Level Visualization and Modeling of U.S. Internal Migration

Introduction

Internal migration shapes housing, labor markets, infrastructure, and communities, yet most public tools are static, single-factor, and hard for non-technical users to explore. We propose an interactive, county-level platform that combines IRS and Census data with modern statistical and machine-learning models to explain and forecast flows. The site will surface net and gross (in/out) movement, expose drivers (housing, labor, demographics), and flag anomalies with uncertainty cues. Built with React/D3/deck.gl and deployed publicly, it provides a fast, transparent, and accessible view of migration.

Despite a multi-decade decline in mobility, internal migration remains central to local labor and housing dynamics (Molloy, Smith, and Wozniak 2011). Recent work ties falling migration to housing costs and labor-market frictions (Olney and Thompson 2024) and shows social networks lower moving costs and steer location choices (Blumenstock, Chi, and Tan 2025; Stuart and Taylor 2021). Additional studies document the long-run decline and regional determinants shaping county flows (Kaplan and Schulhofer-Wohl 2017; Partridge, Rickman, and Ali 2012). Pandemic-era re-sorting further altered county flows (Foster, Fiorio, and Ellis 2024), underscoring the need for timely, exploratory tools at policy-relevant geographies. Classic push–pull framing and demographic determinants remain useful (Urbański 2022; Simpson 2017), but single-factor views miss joint, interacting drivers. IRS county-to-county flows provide long-running, consistent boundaries (Hauer and Byars 2019), allowing contemporary insights to be paired with historical baselines. Most existing dashboards are static and single-factor; national networks become illegible "hairballs," choropleths can mislead with aggregation and color choices, and uncertainty (suppression, margins of error) is rarely visible. Our platform addresses these limits by showing both gross (in/out) and net movement with colorblind-safe, signed encodings; revealing joint drivers via linked map and trend views; and documenting data provenance and uncertainty so users can trust what they see.

Methods

We integrate IRS county-to-county flows (1990–2010; extended with recent vintages as available), ACS 5-year demographics, and economic indicators (e.g., wages/unemployment/income; rents or housing cost proxies). We harmonize to a consistent county geography, carry margins of error through derived estimates, flag suppressed cells, and lag explanatory variables to reduce leakage. The key questions are: where are county net gains/losses accelerating, and by how much; which factors (housing, wages, demographics, network proxies) best explain recent shifts; and which counties exhibit anomalous changes not explained by these factors. Success is measured by predictive fit (Poisson deviance, MAE on log(flow+1)), calibrated uncertainty, and top-K hotspot precision/recall. We target ≤0.25 reduction in Poisson deviance versus OLS gravity on held-out counties, nominal 90% prediction intervals that capture 85–95% of observations, and ≥0.60 top-K precision for emerging net-loss hotspots in the most recent two years.

Baselines include gravity (population, distance; Beine, Bertoli, and Fernández-Huertas Moraga 2016; Poot et al. 2016) and zero-inflated/hurdle Poisson for sparse flows. We then fit ML models (e.g., gradient boosting; neural models with Poisson or zero-inflated losses) to capture nonlinearities and interactions, responding to evidence that standard gravity struggles to predict dynamics out-of-sample (Beyer, Schewe, and Lotze-Campen 2022). We evaluate with time-split backtests and spatial cross-validation (held-out counties/blocks), reporting Poisson deviance, MAE on log(flow+1), calibration, and hotspot metrics. Prior findings that zero-inflated count models can outperform OLS gravity (Morefield and Leslie 2025) motivate our baselines; multilevel variants address county heterogeneity (Xu 2023). Anomalies are flows or county totals where observed values fall outside model prediction intervals given covariates; we compute standardized residuals, adjust for multiple testing across counties, and display flagged counties with brief “why” explanations (top contributing features and uncertainty).

We chose a mapping approach that keeps the picture clear and fast at national scale. At a glance, users see where places are gaining or losing people; as they zoom in, the map reveals more detail without turning into a tangle of lines. Colors are simple and consistent (one for inbound, another for outbound, and a two-color scale for net change), and the legend matches the view. When users hover or click, the map and chart update together, so the numbers always match. Notes on data quality and a “last updated” badge help users trust what they see. The result helps decision-makers quickly answer practical questions—Which counties are losing nurses? Where is housing demand building?—and share findings confidently.

This tool directly serves county planners, housing and transportation agencies, utilities, hospital systems, school districts, and journalists by revealing where and why migration is changing, enabling faster, evidence-based decisions on capacity, siting, and services.

Our visualization stack combines D3 for expressive, coordinated views and WebGL-accelerated layers for scale; this aligns with evidence on robust, interpretable visual encodings (Bostock, Ogievetsky, and Heer 2011; Brewer 1994), de-cluttering dense networks (Holten 2006), communicating uncertainty (MacEachren et al. 2005), and keeping interactions responsive on large datasets (Liu et al. 2013).

Plan & Timeline

Implementation follows a simple pipeline—ingest, harmonize, compute yearly caches, model/forecast, flag anomalies, and serve to the UI. Caches enable fast loading; a scheduled action refreshes data. We version models/data and publish code and documentation openly. The interface provides a left filter panel (year, metric, geography, threshold, demographic slices), a center map (flows or net shading), and a right trend panel (in/out/net history). All views link to a single data source to stay in sync and support colorblind-safe palettes, keyboard navigation, responsive layout, and PNG/CSV export. Evaluation combines model fit and applied utility: top-K hotspot precision/recall for emerging net losses; agreement between anomalies and known shocks (e.g., large employer moves); and task time/accuracy on brief user tests with non-technical stakeholders. Example tasks include "Find three counties with rising net losses since 2020," "Compare two metro areas and list top drivers," and "Export a figure with a short explanation." Risks include weak signal in small counties and many zero flows (we use zero-inflated models and aggregation/smoothing with clear uncertainty cues), spatial dependence that can inflate scores (we apply spatial cross-validation and random effects where needed), and visualization complexity (we offer a "simple mode" for net-only views alongside an "advanced mode").

Midterm checkpoint (week 6): MVP with net choropleth and flow arcs, state/county filters, thresholding, and baseline gravity/ZIP results plus a two-county comparison report. Final exam (week 12): calibrated ZIP/ML models with anomaly flags, linked trend panel, uncertainty/provenance cues, a public demo, and a short user-test summary.

Cost: Data sources are free (IRS/ACS); we build caches locally and host the site on GitHub Pages, keeping compute near zero. Direct costs are 0–100 (domain/incidentals), with effort limited to the project team's time.

A 12-week schedule covers data ingestion and harmonization with baseline models and MVP (weeks 1–4), ML and anomaly detection with uncertainty cues and linked trends (weeks 5–8), and UX polish, small user tests, documentation, and public deployment (weeks 9–12). By semester end, we will deliver a public, county-level migration tool that explains and forecasts flows, surfaces anomalies with uncertainty, and allows non-technical stakeholders to explore "what changed, where, and why." It complements academic work by moving beyond static exhibits to an interactive, trusted platform grounded in sound models and transparent data.

Deliverables

1. Public website with map, trends, filters, download/export. 2) Versioned code repository with cache builder, models, and notebooks. 3) Data catalog listing vintages, sources, and geography notes. 4) Model card with metrics, calibration, and anomaly criteria. 5) Brief user-test summary and a “how to interpret” guide.

References (selected)

Beine, Bertoli, and Fernández-Huertas Moraga (2016); Beyer, Schewe, and Lotze-Campen (2022); Blumenstock, Chi, and Tan (2025); Bostock, Ogievetsky, and Heer (2011); Brewer (1994); Foster, Fiorio, and Ellis (2024); Hauer and Byars (2019); Holten (2006); Kaplan and Schulhofer-Wohl (2017); Liu et al. (2013); Molloy, Smith, and Wozniak (2011); Morefield and Leslie (2025); Olney and Thompson (2024); Partridge, Rickman, and Ali (2012); Poot et al. (2016); Simpson (2017); Stuart and Taylor (2021); Urbański (2022); Xu (2023).