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# On Migration Gravity with Status Quo Bias and Job Search Frictions*

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**Abstract**

Why has internal migration remained low, even as advances in communication technologies have reduced information frictions in relocation decisions? This paper develops and estimates a spatial model of mobility that incorporates status quo bias in locational preferences, multilateral search frictions, and comoving regional unemployment. Using historical proxies for search frictions, we identify and recover county-level estimates of status quo bias across the United States. Status quo bias is spatially heterogeneous and highest in states containing large urban job centers. Translating these estimates into expected-utility, geographic-distance, and state-border equivalents indicates that variation in status quo bias generates migration frictions comparable to large geographic and institutional barriers. Status quo bias also exhibits strong persistence over time, a robust relationship to migration dynamics, and associations with a range of non-wage individual- and community-level correlates of locational preferences (e.g., housing, climate, and religious and political orientations). These patterns suggest that status quo bias partly reflects place-based preferences shaped by individuals' residential histories.

**Keywords:** Migration gravity, status quo bias, and job search networks

**JEL Codes:** J61, J64, R23

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# 1 Introduction

A longstanding feature of the U.S. labor market is the persistently low and declining internal mobility (Basso and Peri, 2020; Molloy et al., 2011, 2016; Dao et al., 2017), despite stark spatial disparities in unemployment and wages. This persistence is puzzling, particularly given the rapid rise of social media as a means of reducing information frictions through interpersonal and group communication.[1] This paper develops a model that integrates search frictions and status quo bias in locational preferences within a unified framework of labor mobility. Conditional on job search frictions, to what extent can low mobility be attributed to status quo bias in locational preferences? Can these estimates uncover previously underappreciated factors – such as community-level political orientation, religiosity, and climate – that shape decisions to migrate or remain in place?

By status quo bias, we refer to the spatial expected-utility premium or discount that a current resident attaches to her own location relative to a potential migrant (Faini and Venturini, 2001). Status quo bias can arise from several sources, including rational responses to switching costs, sunk costs, or information barriers (e.g. Masatlioglu and Ok, 2005; Güney and Richter, 2018),[2] as well as behavioral biases such as framing, endowment, or contextual effects (e.g. Samuelson and Zeckhauser, 1988; Kahneman et al., 1991). These forces generate asymmetric locational preferences between residents and potential migrants, thereby influencing mobility patterns. Because some of these factors may be unobservable to the researcher, a fully rational decision to stay may appear otherwise. Our goal in this paper is to develop a theory that guides the estimation of status quo bias as an umbrella construct encompassing both rational and behavioral mechanisms. We then use these estimates to identify patterns in the data, particularly those related to place-based lived experiences and demographic characteristics, and shed light on the mechanisms underlying status quo bias.

We develop and estimate a search-theoretic model of inter-regional migration flows that accommodates status quo bias in locational preferences in the presence of search frictions. Thus, we depart from the canonical random-utility foundations of the gravity equation with extreme-value-distributed idiosyncratic preferences (Anderson, 2011; Bertoli and Fernández-Huertas Moraga,

[1] A growing literature documents the influence of social media on both internal (Bailey et al., 2018) and international migration (Dekker and Engbesen, 2014; Culora et al., 2021; Spyratos et al., 2019).

[2] These include, for example, prior investments in social capital, friendship and professional networks (Borjas, 1992), information asymmetries between residents and newcomers (Bryan et al., 2014), sunk investments such as housing, schooling, and adaptation to local climate or congestion (Helderman et al., 2006), and cultural affinity or ties to ethnic enclaves (Belot and Ederveen, 2012; Albert and Monras, 2017).

2012), and adopt a framework with simultaneous multilateral Poisson job arrivals as a starting point.[3] This framework allows us to quantify the effects of status quo bias and search frictions on observed migration flows. Job arrival frequencies depend on destination-specific job vacancies and the structure of job search network links, including third-party network linkages that govern the general equilibrium sizes of the job seeker pool in each destination. The job seeker pool in general equilibrium is an important feature because workers can be discouraged from applying to jobs in areas with a competitive job seeker pool (Manning and Petrongolo, 2017). The desirability of a job offer at any given location, on the other hand, is the outcome of a utility draw from a destination-specific distribution. Each worker then maximizes utility by choosing the best option out of all job arrivals, if any. Workers who are not matched with any viable job offer remain in current location as unemployed.

We solve for the equilibrium migration rates between any pair of locations in closed form. The revised migration gravity equation features three parts that expand on their analogues in standard migration gravity equations (Anderson, 2011; Bertoli and Moraga, 2013): (i) bilateral search intensities that capture the strength of bilateral information flow, (ii) origin and destination expected utilities as push and pull forces, incorporating spatial differences in status quo bias, and (iii) a pair of inward and outward multilateral migration resistance terms, also adjusted to account for status quo bias. Multilateral resistance in this context captures the general equilibrium effects of both bilateral and third-party mobility barriers on migration.

The revised migration gravity equation sheds new light on the determinants of mobility. First, mobility depends on the effects of first-hand exposure from individuals' lived experiences – typically unobserved by the researcher – which can manifest as status quo bias in location preference. In addition, bilateral mobility depends on both bilateral and multilateral search frictions, the latter embodying the degree of labor market competition in a destination according to the job search intensity of workers from all third-party locations. Universal improvements in communication technologies are thus a double-edged sword, as information fosters connections between places both bilaterally and multilaterally. With stronger communication links everywhere, gains in any particular bilateral connection are counteracted by a more competitive job market as the effective job seeker pool expands. Thus, broad communication improvements do not necessarily increase mobility (Basso and Peri, 2020; Molloy et al., 2011, 2016; Dao et al., 2017).[4]

[3] Mortensen (2003) provides a single labor market exposition of this job search setting.

[4] We also show that reducing status quo bias in a single location promotes population outflow, whereas reducing it

Furthermore, the revised gravity equation shows how equilibrium bilateral mobility co-moves with unemployment. In canonical structural migration gravity equations based on random utility choice framework with no involuntary unemployment, a population product term and a normalized bilateral migration cost term govern mobility between any two places (e.g. Anderson, 2011). In our setting, we find that the population product term requires a revision when search-frictions induced unemployment are at play. The new population product term includes (i) sending location employment inclusive of emigrants, which is proportional to one minus the unemployment share at origin, and (ii) destination employment inclusive of all immigrants, which takes into account the unemployment shares in all third party sending locations. Since the unemployment rate is the share of job seekers who fail to find a job anywhere, it both drives and is driven by the forces of migration.

Taken together, the revised gravity equation thus sheds light on the biases that can come into play when estimating migration gravity without regard for spatial differences in status quo bias, multilateral search frictions, or unemployment. With these challenges in mind, we show how we can nonetheless consistently estimate the revised gravity model, using U.S. bilateral county-level migration data from the American Community Surveys (ACS) as a case in point. To control for job search frictions we first account for spatial distances and state border effects. Using the 1940 full-count Census records, we then construct three historical county-pair dissimilarity indices as normalized Euclidean distance terms respectively for ethnicity, industry-of-employment and occupation compositions. We use historical composition shares to ensure that search frictions proxies are not driven by the migration flows we observe. Guided by the literature, the strength of county-to-county distance as well as ethnicity, occupation and industry-of-employment dissimilarities are our primary proxies for the degree of job search frictions. These embody job search frictions that are mediated by geographic distance (e.g. Manning and Petrongolo, 2017; Kone et al., 2018), family and friendship network links (e.g. Chau, 1997; Munshi, 2003; Mahajan and Yang, 2020) industry as well as occupational connections (e.g. Chen and Rosenthal, 2008; Bryan and Morten, 2019; Schmutz and Sidibé, 2018) that facilitate job search and relocation.[5]

We present three applications of our empirical framework. First, we examine the role of historical search-frictions controls in shaping current interregional mobility across three variants of

everywhere can have the opposite effect on mobility between specific locations whenever the multilateral impacts of status quo bias on job competitiveness dominate the improvement in any particular bilateral link.

[5]We also show that county-to-county present day friendship connections, as measured by the population normalized counts of Facebook links, is well explained by our suite of distance-, border-, and historical dissimilarity controls.

the migration gravity specification: (i) outflow-ratio gravity (outflow as a share of non-movers), (ii) inflow-ratio gravity (inflow as a share of non-movers), and (iii) the geometric mean of the two. Empirical studies of migration and trade gravity models employ similar formulations, including outflow-based gravity (e.g., Eaton and Kortum, 2002; Artuç et al., 2010) and geometric-mean gravity (e.g., Head and Ries, 2001). Our model accommodates all three types of gravity specifications, and then points out how to interpret location fixed effects in each setting. To wit, in outflow gravity, location fixed effects represent relative expected utilities, whereas in inflow gravity, the location fixed effects have a relative employment interpretation.

These location fixed effects motivate a second application, in which we leverage the fact that each location in our data set is both an origin and a destination. Our theory predicts that county-level status quo bias estimate can be ascertained as the difference between origin and destination fixed effects of the same county.[6] Since origin and destination fixed effects absorb any county-level barriers to migration not accounted for by search frictions controls, search related barriers to migration may be misattributed as status quo bias if the list of search frictions control is erroneous. Thus, we separately examine the mobility determinants between highly populated counties that are home to major urban job hubs, and the mobility determinants between smaller counties typically with far fewer bilateral migrants.

Using county-to-county migration data from the American Community Survey (ACS) for three 5-year periods (2005–2009, 2014–2018, and 2015–2019), we estimate outflow-ratio, inflow-ratio, and geometric-mean migration gravity regressions to assess both decadal (2005–2009 to 2015–2019) and year-on-year (2014–2018 to 2015–2019) variations in status quo bias. We find that county-level status quo bias is highly dispersed and that this dispersion has increased over the decade. A one-standard-deviation increase in log status quo bias has the same effect on the migration outflow ratio as a 39% reduction in the expected utility ratio, or an increase of 1,136 miles in distance between destination and origin counties. The difference in the migration ratio between otherwise identical in-state and out-of-state counties is equivalent to an interquartile-range increase in log status quo bias. These behavioral equivalents suggest that status quo bias generates migration frictions comparable to large geographic and institutional barriers.

We also find that county-level status quo bias estimates are strongly positively correlated over

[6] In a world without status quo bias, these two fixed effects should coincide since they both represent the expected utility proxy of the same location. With positive (negative) status quo bias, expected utility as seen by residents will be strictly greater (less) than that of new migrants.

time, suggesting that they reflect persistent or structural differences in community characteristics across counties that asymmetrically tilt the locational preferences of residents and newcomers. These observations motivate a third application, in which we assess the extent to which status quo bias contribute to explaining the intensity of county-to-county migration in the United States. Specifically, we re-estimate the migration gravity equations using historical status quo bias estimates from a decade earlier as controls. Using Shapley value $R^2$ decomposition, we find that historical status quo bias (2005–2009) accounts for 5% to 8% of the $R^2$ in migration gravity regressions for 2014–2018 and 2015–2019. We interpret these figures as lower-bound estimates of the impact of contemporaneous status quo bias on migration, due to coefficient attenuation that may arise when the historical controls are noisy proxies for future status quo bias.

To investigate the place-based forces and population characteristics that drive county-level differences in status quo bias, we correlate status quo bias estimates with a wide array of county-level controls, quantifying associations using Least Absolute Shrinkage and Selection Operator (LASSO) regression. We find that status quo bias estimates – based on both outflow and inflow gravity models – are systematically correlated with features of local economies that are often overlooked in migration gravity research but are closely related to job mobility, skills, age, and other effects of first-hand exposure due to lived experiences. These include investments to adapt to local conditions, preferences for living in locations with shared identity, and local ties developed through interpersonal interactions and services. In particular, community-level characteristics such as climate, political orientation, and religiosity are positively associated with status quo bias. These findings complement known factors, such as public goods and amenities (e.g., Boustan, 2013; Albouy and Stuart, 2014), highlighting novel community-level correlates that strengthen individuals' attachment to their communities.

## 2 Related Literature

This paper contributes to several areas of research. First, we provide a micro-founded migration gravity equation in a search-theoretic setting with simultaneous multilateral Poisson job arrivals. The gravity model is one of the most widely adopted empirical models for bilateral migration (Ramos, 2016).[7] Our work demonstrates that the closed-form gravity can be preserved with the

[7]The literature has identified a wide range of bilateral migration determinants, including for example economic disparities (Docquier et al., 2014), state border barriers (Kone et al., 2018), environmental stress (Cattaneo and Peri,

addition of search frictions determinants, while allowing for a more informative interpretation of estimated coefficients, such as status quo bias. We also contribute to recent applications of general equilibrium models where production and multilateral labor mobility interact (e.g. Artuç et al., 2010; Artuç and McLaren, 2015; Caliendo et al., 2019; Tombe and Zhu, 2019). By empirically verifying the relevance of historical search friction controls on migration and the importance of status quo bias, we demonstrate that mobility shapes and is shaped by the spatial spread of different types of job search network links across space and time. This mechanism naturally implies path-dependence in general equilibrium outcomes when inter-regional mobility is part of the story (Chau, 1997; Kerr et al., 2017).

Our work is also related to a nascent literature that incorporates search frictions into spatial general equilibrium models (e.g. Schmutz and Sidibé, 2018; Heise and Porzio, 2019).[8] In these models, migration is guided by optimal on-the-job search, where at each point in time, workers compare a random job arrival with their current employment state. These frameworks have been applied to the French and German labor markets to shed light on the implied cost of migration, and the sources of regional wage gaps. Our approach differs from these studies in several important respects. By accommodating simultaneous random job arrivals from any number of destinations, our model can rationalize and replicate the closed-form gravity, provide exact guidance on how to interpret inflow and outflow gravity estimates, and show that location fixed effects, when appropriately compared, admit a status quo bias interpretation.[9]

Finally, mobility in our setup is driven by individual cost-benefit considerations conditional on origin- and destination-specific characteristics and individual preferences. Clearly, alternative drivers exist, including mobility driven by a desire to improve access to jobs (Harris and Todaro, 1970), individual differences in locus of control (Caliendo et al., 2019), environmental stress and congestion forces (Feng et al., 2012; Cattaneo and Peri, 2016), retirement relocation (King et al., 2021), and other long-term dynamic migration motivations (Artuç et al., 2010; Dustmann and Glitz, 2011; Caliendo et al., 2019) to name just a few. Our focus is instead to develop a static labor

2016), language and cultural barriers (Belot and Ederveen, 2012; Adserà and Pytliková, 2015), to name a few.

[8]Our frameworks, which features search frictions induced involuntary unemployment, also differs from other models of mobility with non-employment (e.g. Caliendo et al., 2019), where non-employment occurs in a dynamic model with perfect foresight, no history-induced path dependency, and extreme value distributed random preference shocks.

[9]Heise and Porzio (2019) incorporates locational preference for East and West Germany depending on birth region – referred to in the paper as home bias. This taste bias by birth region is akin to the optimal sequencing migration model of Kennan and Walker (2011), which also allows for a bias in favor of a worker's childhood location (measured as the state of residence at age 13). Our status quo bias term addresses expected utility evaluations asymmetries by current residents and newcomers, and not a birthplace-driven preference shift.

market equilibrium model of mobility with search frictions and status quo bias. This approach allows us to make block-by-block comparison with a long history of other models of migration gravity in the static context but without search frictions or status quo bias (e.g. Ahlfeldt et al., 2015; Morten and Oliveira, 2016; Amior and Manning, 2018; Monte et al., 2018; Tombe and Zhu, 2019). In addition, as we will show below, some of these alternative drivers, such as climate, congestion, proximity to family, are in fact embedded as correlates of our status quo bias estimates.

# 3 Model

We consider the migration decisions of $N_m$ job seekers in each of $M$ locations, with total population $N = \sum_{m=1}^{M} N_m$.[10] Let $v_n > 0$ denote the number of employment vacancies in destination $n = 1, ..., M$. Search frictions prevent job seekers in origin $m$ from sampling all $v_n$ jobs in destination $n$. The number of job offers a worker receives from destination $n$, $z_n = 0, 1, 2, ...$, follows a Poisson distribution with parameter $\lambda_{mn} \geq 0$.[11]

$$\Pr(z_n;\ \lambda_{mn}) = \frac{exp\left(-\lambda_{mn}\right)\left(\lambda_{mn}\right)^{z_n}}{z_n!}.$$

The job arrival rate $\lambda_{mn}$ depends on three factors: (i) the search intensity of workers from $m$ in $n$, $a_{mn} \geq 0$; (ii) the number of vacancies $v_n$; and (iii) the total effective job seekers in destination $n$, $J_n = \sum_{k=1}^{M} a_{kn} N_k > 0$, which accounts for search intensity from all $M$ locations. The job arrival rate is defined as follows:[12]

$$\lambda_{mn} = \frac{a_{mn} v_n}{\sum_{k=1}^{M} a_{kn} N_k} \equiv \frac{a_{mn} v_n}{J_n}. \tag{1}$$

$a_{mn}$ captures the level of search intensity of workers in $m$ for jobs in $n$ and parameterizes the extent of search frictions. Difficulties in job search due to distance can be offset by social or career networks, whereas geographic and institutional barriers, such as distance and state boundaries, can intensify search frictions.[13] In the absence of cross-location barriers, we assume that $a_{mm} =$

[10] Job search takes place at an individual's origin location, as in Schmutz and Sidibé (2018). We assume that individuals are knowledgeable about other locations before migration, following Kaplan and Schulhofer-Wohl (2017).

[11] All workers in origin $m$ are assumed to share the same job arrival intensity $\lambda_{mn}$. This assumption can be relaxed by partitioning $m$ into sub-locations $m_i$, with each sub-location having its own intensity $\lambda_{m_i n}$; the model solution generalizes accordingly.

[12] The specification in (1) satisfies adding-up, since $\sum_{k=1}^{M} \lambda_{kn} N_k = \sum_{k=1}^{M} a_{kn} N_k \frac{v_n}{J_n} = v_n$.

[13] We model $\lambda_{mn}$ as a multi-destination analogue of the canonical job arrival rate in models of job search with one single location, $v_m / N_m$ (e.g. Mortensen 2003).

$a_{nn} = a$.[14]

All else equal an increase in $a_{mn}$ raises job arrival $\lambda_{mn}$. By contrast, an increase in search intensity from workers in another location, $a_{kn}$ for $k \neq m$, reduces $\lambda_{mn}$ as it raises the intensity of job competition in $n$ with other job seekers. This increased competition is captured by the effective number of job seekers in $n$, $J_n \equiv \sum_k a_{kn} N_k$, which rises with $a_{kn}$.

We assume that the utility of living in location $n$ for a worker from $m$ is random and specific to each vacancy-worker match. This utility accounts for wages and non-wage benefits such as amenities.[15] The probability distribution of this match-specific utility in location $n$, $\omega$, is characterized by a cumulative distribution function $F_{nn}(\omega) = F_n(\omega, 1)$ for workers native to $n$.

We allow migrant workers to have different utility perceptions relative to natives, with distribution function $F_{mn}(\omega) = F_n(\omega, 1 + b_n)$, $m \neq n$, where we assume the following first-order stochastic ordering:

$$F_n(\omega, 1 + b_n) \geq F_n(\omega, 1) \tag{2}$$

whenever $b_n \geq 0$. Put another way, positive (weakly negative) status quo bias exists if and only if $b_n \geq (<) 0$.[16]

Specifically, we assume that the distribution function follows a power law form. The power law has been shown to fit income distributions well in the United States and other countries (e.g. Armour et al., 2016; Atkinson, 2017; de Vries and Toda, 2022).[17] We model $F_n(\omega, \cdot)$ as a scaled generalized Pareto distribution,[18]

$$F_n(\omega, 1) \quad = \quad 1 - w_n \left(1 + \epsilon\omega\right)^{-1/\epsilon}, \quad \text{if } m = n \tag{3}$$

for $\omega \geq 0$, where $(1 + \epsilon\omega)$ satisfies the power law. Variations in the scale parameter $w_n \in (0, 1]$ creates first order stochastically dominating shifts in the distribution function. $\epsilon < 1$ is a shape

[14] Destination-specific differences in expected utilities, which can embody barriers to landing a good job, are modeled in equation (2).

[15] Random destination utilities is a common assumption in the mobility literature. See for example, Bertoli and Moraga (2013), Dix-Carneiro (2014), Monte (2015), Redding (2016).

[16] As in Samuelson and Zeckhauser (1988), status quo bias here reflects a "tendency to adhere to status quo choices more frequently than would be predicted by the canonical model" where migration exhibits no path dependence, due for example to the absence of sunk investment, adaptation to local conditions, and social network development.

[17] A variable $x$ satisfies the power law if the probability $Pr(x \geq \bar{x})$ is proportional to $x$ raised to a constant exponent.

[18] The generalized Pareto distribution class is commonly used in extreme value theory (Balkema and de Haan, 1974; Coles et al., 2001). Special cases include the exponential and standard Pareto distribution.

parameter. Also let

$$F_n(\omega, 1+b_n) \quad = \quad 1 - \frac{w_n}{1+b_n}\,(1+\epsilon\omega)^{-1/\epsilon}\,, \;\; \text{if} \;\; m \neq n. \tag{4}$$

where $b_n \geq 0$ is also a shift parameter. The expected values of $\omega$ associated with $F_n(\omega, 1)$ and $F_n(\omega, 1+b_n)$ are $w_n(1-\epsilon)^{-1} > 0$ and $w_n[(1-\epsilon)(1+b_n)]^{-1} > 0$ respectively.

Given equation (3), the mass of probability draws evaluated at $\omega = 0$ is equal to $1 - w_n$. Thus, $1 - w_n$ represents the share of individuals who, by the law of large numbers, fail to obtain any strictly positive utility draws in destination $n$, conditional on a vacancy-worker match. This share decreases as the expected utility of the destination $w_n/(1-\epsilon)$ improves, for a given $\epsilon$.

Unemployment can occur in this model for two reasons: (i) workers fail to find a match with a vacancy due to search frictions parameterized by $\lambda_{mn}$; or (ii) workers do not obtain a strictly positive utility draw anywhere conditional on having at least one vacancy match. The model captures the latter possibility via the parameter $w_n$: the likelihood of not finding a viable (strictly positive) utility draw decreases as the expected desirability of location $n$, or equivalently $w_n$, increases.

In the appendix, we discuss alternative distributional assumptions.[19] More generally, the model can be solved for any class of distribution functions $F_n(\omega, \cdot)$ that (i) share a common minimal utility $\underline{\omega} \geq 0$, and (ii) satisfy the power law. Under these conditions, the gravity setting that we derive below is robust to variations in the functional form assumptions on $F_n(\omega, \cdot)$.

From equation (4), the positive status quo bias term $b_n$ represents the spatial expected utility premium that a local resident attaches to her origin relative to a newcomer (Faini and Venturini, 2001). Equivalently, $b_n$ can be interpreted as the expected utility discount that a newcomer applies to moving to $n$. Native and prospective residents may evaluate the same location differently due to sunk investments, adaptation to local conditions, and information about the local environment that takes time to acquire.[20]

At each destination $n$, the cumulative distribution function of the maximal utility draw by a

[19] For example, a standard Pareto distribution $P_n(\omega) = 1 - (\omega/w_n)^{-1/\epsilon}$, for $w_n > 0$ and $\epsilon < 1$, also satisfies the power law and imposes a strictly positive lower bound for each destination, $w_n$. Imposing a common lower bound utility draw $\underline{\omega} \geq \max\{w_1, ..., w_N\} > 0$, yields the distribution $P(\omega, w_n) = 1 - (\omega/w_n)^{-1/\epsilon}$ for $\omega \geq \underline{\omega} > w_n$, and $P(\omega, w_n) = 0$ otherwise. As with $F_n(\omega; \cdot)$ in equation (4), the measure of individuals who receive the minimal utility draw $\underline{\omega}$ in this Pareto variant is $1 - (\underline{w}/w_n)^{-1/\epsilon} > 0$, which decreases with $w_n$.

[20] Sources of status quo biases are many (Samuelson and Zeckhauser, 1988), including prior investment in social capital and to local friendship networks (Borjas, 1992), information asymmetries between residents and potential migrants (Bryan et al., 2014), sunk investments such as housing or schooling (Helderman et al., 2006), and cultural affinity or ties to ethnic enclaves (Belot and Ederveen, 2012; Albert and Monras, 2017).

worker from origin $m$ is:

$$p_{mn}(\omega) \equiv \sum_{z_n=0}^{\infty} \frac{exp\left(-\lambda_{mn}\right)\left(\lambda_{mn}\right)^{z_n} F_{mn}(\omega)^{z_n}}{z_n!} = exp\left[-\lambda_{mn}(1 - F_{mn}(\omega))\right]. \quad (5)$$

$p_{mn}(\omega)$ is the probability that the highest utility job offer received by a worker does not exceed $\omega$.

Each worker then maximizes utility by selecting the best option among all job offers received, if any. Workers who do not receive any offer with strictly positive utility remain in their origin location as unemployed. Substituting the distribution assumptions above into $F_{nn}$ and $F_{mn}$, the distribution of the highest offer for a worker from $m$ in destination $n$ is:

$$\begin{aligned} p_{mn}(\omega) &= exp\left[-\lambda_{mn}(1 - F_{mn}(\omega))\right] \\ &= \exp\left[-\lambda_{mn} w_n (1 + b_n)^{-\mathbb{I}_{mn}} (1 + \epsilon\omega)^{-1/\epsilon}\right] \end{aligned} \quad (6)$$

where $\mathbb{I}_{mn}$ is an indicator equal to $1$ if $m \neq n$, and zero otherwise. (6) shows that the distribution $p_{mn}(\omega)$ of the best offer received by a worker from $m$ in destination $n$ takes the functional form of a generalized extreme value distribution function,[21] with parameters $\lambda_{mn}$, and $w_n(1 + b_n)^{-\mathbb{I}_{mn}}$. An increase in search intensity through a higher $\lambda_{mn}$, and a higher expected utility in $n$ through $w_n(1 + b_n)^{-\mathbb{I}_{mn}}$, both generate first order stochastically dominating shifts in the distribution of the best offer from $n$, all else equal.

### 3.1 The Decision to Migrate

Denote by $\mu_{mn}$ the probability that a worker from $m$ finds that the best utility draw in $n$, $\omega_{mn}$, more appealing than the best offers from any one of the $M - 1$ locations's best offers, $\omega_{mk}$, $k \neq n$. Thus

$$\mu_{mn} = \int_0^{\infty} Pr\left[\omega \geq \left\{\max_{k \neq n} \omega_{mk}\right\}\right] dp_{mn}(\omega).$$

Let $\alpha_{mn}$ denote the status quo bias adjusted search intensity

$$\alpha_{mn} \equiv a_{mn}\left(1 - \frac{\mathbb{I}_{mn} b_n}{1 + b_n}\right) \quad (7)$$

[21] Many commonly used extreme value distributions such as Fréchet, Gumbell and Weibull distributions are special cases of the generalized extreme value family. For example, the Fréchet distribution obtains by setting $\lambda_{mn} w_n (1 + b_n)^{-\mathbb{I}_{mn}}$ to unity, and applying the change of variables $y = (1 + \epsilon\omega)$, and $\beta = 1/\epsilon$, so that $F(y) = \exp(-y^{-\beta})$.

where the contribution of status quo bias to migration frictions when $m \neq n$ is made explicit. Define $W_n$ as the employment-adjusted expected utility of location $n$ where

$$W_n = \frac{w_n v_n}{J_n} = \frac{w_n v_n}{\sum_k a_{kn} N_k}. \tag{8}$$

Now, by the law of large numbers, $\mu_{mn}$ represents the fraction of the workers in $m$ who prefers location $n$ to any of the other $M-1$ locations.[22]

$$\begin{aligned} \mu_{mn} &= \int_0^\infty \prod_{k \neq n} p_{mk}(\omega) dp_{mn}(\omega) \\ &= \left( \frac{\alpha_{mn} W_n}{\sum_{i=1}^M \alpha_{mi} W_i} \right) \left( 1 - exp \left[ - \sum_{i=1}^M \alpha_{mi} W_i \right] \right). \end{aligned} \tag{9}$$

The expression, $\sum_{i=1}^M \alpha_{mi} W_i \equiv O_m$,[23] normalizes bilateral search intensity $\alpha_{mn}$ to account for the job opportunities in all other locations that affect the relative desirability of $n$ for workers in $m$. In particular, high search intensities in locations other than $n$, or high $\alpha_{mi}, \quad i \neq n$, reduce the likelihood of migration from $m$ to $n$. Similarly, higher expected utilities in alternative locations (i.e., high $W_i,\ i \neq n$), also lower the likelihood of migration from $m$ to $n$. The term $O_m$ is referred to as outward multilateral resistance (Anderson, 2011; Bertoli and Moraga, 2013), and captures the idea that bilateral mobility depends on the average ease of job search in third-party locations weighted by the corresponding expected utility.

**Proposition 1.** *Bilateral mobility rates from $m$ to $n$, $\mu_{mn}$, depend on (i) bilateral status quo bias adjusted search intensities $\alpha_{mn}$, (ii) destination expected utility $W_n$, and (iii) the outward multilateral resistance term $O_m$:*

$$\mu_{mn} = \alpha_{mn} W_n (1 - \exp(-O_m))/O_m.$$

[22] This follows since,

$$\lambda_{mn} w_n = \frac{a_{mn} v_n}{\sum_k a_{kn} N_n} (1 - b_n \mathbb{I}_{mn}/(1 + b_n)) w_n = \alpha_{mn} W_n$$

by definition of $\lambda_{mn}$ in (1), $\alpha_{mn}$ in (7), and $W_n$ in (8). Thus

$$\begin{aligned} \int_0^\infty \prod_{k \neq n} p_{mk}(\omega) dp_{mn}(\omega) &= \int_0^\infty \alpha_{mn} W_n (1 + \epsilon\omega)^{-1/\epsilon - 1} \exp \left[ \sum_{k=1}^M \alpha_{mk} W_k (1 + \epsilon\omega)^{-1/\epsilon} \right]) d\omega \\ &= \left( \frac{\alpha_{mn} W_n}{\sum_{i=1}^M \alpha_{mi} W_i} \right) \left( 1 - exp \left[ - \sum_{i=1}^M \alpha_{mi} W_i \right] \right) \end{aligned}$$

where the last equality follows by definition of $p_{mn}(\omega)$.

[23] To see this, denote the inverse of search intensity as migration frictions, say $t_{mn} = 1/\alpha_{mn}$. The term $O_m \equiv \sum_{i=1}^N W_{mi}/t_{mi}$ corresponds to what Anderson (2011) refer to as outward migration friction in a search frictions free world.

In this model of mobility with multilateral job search frictions, unemployment and migration are jointly determined. The number of workers from location $m$ who become employed is directly related to the outward multilateral resistance term

$$\begin{aligned}\sum_{n=1}^{M}\mu_{mn}N_m &= \left(1-exp\left[-\sum_{i=1}^{M}\alpha_{mi}W_i\right]\right)N_m \\ &= [1-\exp(-O_m)]N_m \equiv (1-u_m)N_m\end{aligned}$$

where the unemployment share in location $m$ – the fraction of workers in location $m$ who search for a job but fail to find one – is uniquely captured by outward multilateral resistance:[24]

$$u_m = \exp(-O_m). \tag{10}$$

(10) highlights interregional determinants of local unemployment. Since $O_m = \sum_{i=1}^{M}\alpha_{mi}W_i$, unemployment in location $m$, $u_m$, is a function of search effectiveness in all of the potential destination locations. In particular, unemployment reflects bilateral search intensities $\alpha_{mi}$ weighted by the corresponding expected utility of location $i$, $W_i$.

### 3.2 Structural Gravity with Unemployment

It is useful to express (9) as a structural migration gravity equation. In this form, migration and unemployment appear explicitly as co-moving outcomes of population stocks and migration triggers. Before presenting the structural equations, note that they feature two expressions that capture the role of multilateral job search in shaping mobility and overall employment. First, the outward multilateral resistance term for each origin $m$, $O_m = \sum_{i=1}^{M}\alpha_{mi}W_i$, summarizes the average ease of job search $\alpha_{mi}$ across all potential destinations $i$ weighted by the expected utility of location $i$ ($W_i$) experienced by workers from origin $m$. Second, inward multilateral resistance for each destination $n$ reflects the average ease of job search across all origin locations for workers seeking jobs in destination $n$, weighted by the relative availability of employment opportunities in each $m$.

To see this, let $M_{mn} = \mu_{mn}N_m$ denote total migration from $m$ to $n$, and $L_n = \sum_m M_{mn}$ denote

[24] Note that the share of unemployed job seekers differ slightly from the unemployment rate defined in the standard way (total number of unemployed individuals as a share of the total labor force) as the denominator in $u_m$ includes outflows of prior residents and does not include inflows of migrants from other locations.

total employment in $n$:[25]

$$M_{mn} = \frac{\alpha_{mn}}{O_m I_n} \frac{L_n \times [N_m(1-u_m)]}{\sum_i N_i(1-u_i)}. \tag{11}$$

where $I_n$ denotes multilateral resistance, capturing the migration friction affecting potential arrivals to destination $n$, with

$$I_n = \sum_m \frac{\alpha_{mn}}{O_m} \frac{N_m(1-u_m)}{\sum_i N_i(1-u_i)}. \tag{12}$$

Similarly, outward multilateral resistance for origin $m$ is given by

$$O_m = \sum_n \alpha_{mn} W_n = \sum_n \frac{\alpha_{mn}}{I_n} \frac{L_n}{\sum_i N_i(1-u_i)}. \tag{13}$$

Thus, total migration between two locations depends on three main components: (i) bilateral status quo bias adjusted search intensity $\alpha_{mn}$ normalized by both outward and inward multilateral resistance ($O_m$ and $I_n$), (ii) a population product, reflecting the total number of employed workers native to $m$, $N_m(1-u_m)$, and the total number of employed workers (inclusive of migrants) in $n$, $L_n = \sum_m M_{mn}$, and (iii) normalization by the overall employment level $\sum_i N_i(1-u_i)$.

Several observations are in order. First, we ask how migration depends on the stock of labor force in the origin and in the destination when equilibrium unemployment co-exists with migration. Equation (11) prescribes the product of key population / workforce indicators as a determinant: the number of employed sending location workers $N_m(1-u_m)$ (inclusive of outward migrants) applies, and total labor supply in $n$, $L_n$. Here $L_n = \sum_k \mu_{kn} N_k = \sum_k \alpha_{kn} W_n (1-u_k) N_k / O_k$ accounts for inward migrants.

Second, consider the special case where the search intensities are symmetric across all locations

[25] The steps are exactly analogous to the structural trade gravity equation in Anderson (2011) and relegated to Appendix A.

$\alpha_{mn} = \alpha > 0$. Bilateral mobility simplifies to[26]

$$M_{mn} = \frac{N_m L_n}{N}. \tag{15}$$

With universal symmetry in search intensity after adjusting for status quo bias, the fraction of workers from $m$ in all destinations is equal to its share of workers in total population ($M_{mn}/L_n = N_m/N$). Furthermore, mobility defined as the share of migrants from $m$ to $n$ in $m$'s total population is equal to the share of employed workers in $n$ in total population

$$\frac{M_{mn}}{N_m} = \frac{L_n}{N} \tag{16}$$

These are directly analogous to the migration friction and search frictions free counterparts, even though search frictions remains and unemployment prevails. The reason for these observations is that with symmetric search intensity, unemployment shares are the same everywhere for outward multilateral migration resistance is:

$$O_m = \alpha \sum_n W_n = \frac{\sum_n v_n w_n}{N} = O$$

for all $m$. This reiterates the fact that when search intensities are identical, workers in any location have equal access to jobs anywhere. The symmetric mobility ratios in (15) thus naturally follow.

Third, consider a proportionate improvement in communication technology across all locations by a factor of $\gamma > 1$ everywhere. Unemployment is unaffected by this improvement since

$$O_m = \sum_n \frac{\gamma \alpha_{mn} v_n w_n}{\sum_k \gamma \alpha_{kn} N_k} = \sum_n \frac{\alpha_{mn} v_n w_n}{\sum_k \alpha_{kn} N_k}$$

since rising search capabilities is matched with a rise in job competition in every location through

[26]To see this, note that outward multilateral migration resistens simplifies to

$$O_m = \alpha \sum_n W_n = \frac{\sum_n v_n w_n}{N}$$

for all $m$ and thus both $O_m$ and unemployment shares will be equalized across all origins, with $u_m = u$. Furthermore, and once again under symmetry $\alpha_{mn} = \alpha$, the inward multilateral resistance:

$$I_n = \sum_m \left(\frac{1}{\sum_i W_i}\right)\left(\frac{N_m}{\sum_i N_i}\right) = \sum_m \left(\frac{1}{\sum_i W_i}\right)\frac{N_m}{N} = I. \tag{14}$$

and thus $I_n$ will also be equalized across all destinations. Moreover, the product of the inward and outward multilateral resistance can be simply expresed:

$$OI = \alpha$$

from (12) and (13). (15) obtains upon substituting these expressions in (11).

$J_n$. Consequently, improvements in communication technologies do not guarantee rising employment, nor does it guarantee rising mobility, since

$$\begin{aligned}\mu_{mn} &= \int_0^\infty \prod_{k\neq n} p_{mk}(\omega) dp_{mn}(\omega) \\ &= \left(\frac{\alpha_{mn} v_n w_n / J_n}{\sum_{i=1}^M \alpha_{mi} v_i w_i / J_i}\right)(1-u_m).\end{aligned}$$

is likewise invariant to equi-proportionate increases in $\alpha_{mn}$ for the same reason. We have thus:

**Proposition 2.** *Symmetric proportionate improvements in search intensity everywhere have no impact on bilateral migration, either as a share of destination $n$ employment ($M_{mn}/L_n$), or as a share of origin $m$ employment ($M_{mn}/[N_m(1-u_m)]$). Such improvements also do not affect the unemployment share $u_m$.*

Proposition 2 speaks to the puzzling observation of low levels of labor mobility in the US and elsewhere (Basso and Peri, 2020), despite advances in information and communication technology and the growing ease of long distance interpersonal communication. A direct implication of this result is that across-the-board incentives that increase job search effectiveness have an ambiguous effect on bilateral migration intensities ($\mu_{mn}$) because such incentives raise both the attractiveness of migration ($\alpha_{mn}$), while also raising the ease of finding a job in third party locations $\alpha_{mi}$. The main takeaway is that only a disproportionate improvement in job search intensity $\alpha_{mn}$ will raise mobility between $m$ and $n$. Likewise, since

$$\mu_{mn} = \left(\frac{\alpha_{mn} W_n}{\sum_{i=1}^M \alpha_{mi} W_i}\right)\left(1 - exp\left[-\sum_{i=1}^M \alpha_{mi} W_i\right]\right).$$

from equation (9), where $\alpha_{mn} = a_{mn}/(1+b_n)$, a targeted subsidy that raises $W_n$ to $W_n(1+s_n)$, can offset high status quo bias $(1+b_n)$, low expected utility $W_n$, or high search friction (low $a_{mn}$). These targeted subsidies are more effective than across-the-board relocation subsidies in driving migration.

## 4 Applications

We now have an estimable model of migration gravity in which heterogeneous search intensity ($a_{mn}$), expected utility ($W_i$), status quo bias ($b_i$), multilateral search frictions captured by $O_m$, and unemployment $(u_i)$ are simultaneously incorporated. In the following applications, we examine empirically the role of search intensity on migration, the meaning of location fixed effects, and in turn we illustrate how the degree of status quo bias can be backed out using origin and destination fixed effects. These estimates can then allow for an evaluation of the contribution of status quo bias to variations in migration rates between county pairs in the United States.

**Outflow Gravity, Inflow Gravity and Geometric Mean Gravity**

The migration gravity model in (9) can be estimated in a number of ways (Anderson and van Wincoop, 2004). We start by adopting a sending location perspective as also adopted in Artuç et al. (2010),[27] and consider the outflow of migrants as a share of workers who are left behind, henceforth outflow gravity. From equation (9)

$$\frac{\mu_{mn}}{\mu_{mm}} \;=\; A_{mn}\left(\frac{W_n}{W_m}\right)\left(\frac{1}{1+b_n}\right), \;\; m \neq n. \tag{17}$$

where $A_{mn} \equiv a_{mn}/a$. Three sets of push and pull forces are featured in (17): (i) the search intensities $A_{mn}$, (ii) the ratio of destination to sending-location expected utilities $W_n/W_m$, and (iii) status quo bias at destination $n$. Taking logs on both sides, we obtain a migration gravity model of worker outflows, henceforth outflow gravity. For any $n \neq m$,

$$\ln \mu_{mn} - \ln \mu_{mm} = \ln A_{mn} - T_m + D_n, \tag{18}$$

where sending and receiving location fixed effects ($T_m = W_m$ and $D_n = W_n/(1+b_n)$) have expected utility interpretations as perceived by local residents at sending locations $W_m$, and by potential migrants at destination locations $W_n/(1+b_n)$.

Analogously, let inflow gravity denote the inflow of migrants as a share of employed destination non-movers:

$$\frac{\mu_{mn}}{\mu_{nn}} = A_{mn}\left(\frac{(1-u_m)\ln(1/u_m)}{(1-u_n)\ln(1/u_n)}\right)\left(\frac{1}{1+b_n}\right). \tag{19}$$

The push and pull factors associated with inflow gravity are (i) the search intensities $A_{mn}$, and (ii) relative employment rates $[(1-u_m)\ln(1/u_m)]\,/\,[(1-u_n)\ln(1/u_n)]$, and (iii) status quo bias at destination $n$.

$$\ln \mu_{mn} - \ln \mu_{nn} = \ln A_{mn} + t_m - d_n, \tag{20}$$

where sending and destination fixed effects $t_m = (1-u_m)\ln(1/u_m)$ and $d_n = (1-u_n)\ln(1/u_n)(1+$

[27] See Mayer and Head (2002) and Eaton and Kortum (2002) applications in international trade.

$b_n$) have employment interpretations.

Finally, take the geometric mean between the outflow and inflow gravity equations,

$$\frac{\mu_{mn}}{\sqrt{\mu_{nn}\mu_{mm}}} = A_{mn}\left(\frac{W_m}{(1-u_m)\ln(1/u_m)}\right)^{-0.5}\left(\frac{W_n}{(1-u_n)\ln(1/u_n)}\right)^{0.5}\left(\frac{1}{1+b_n}\right). \tag{21}$$

Geometric mean gravity jointly accounts for expected utilities $W_m$ and $W_n$ and relative employment prospects $(1-u_m)\ln(1/u_m)$ and $(1-u_n)\ln(1/u_n)$ as the drivers of migration. Importantly, even in the geometric mean formulation, status quo bias appears in a similar way in equation (21) as in equations (17) and (19) where $(1+b_n)$ is a log-additive term. Thus taking logs,

$$\ln\mu_{mn} - 0.5\left(\ln\mu_{nn} + \ln\mu_{mm}\right) = \ln A_{mn} - \tau_m + \delta_n, \tag{22}$$

There are two important takeaways. First, outflow gravity ($\mu_{mn}/\mu_{mm}$), inflow gravity ($\mu_{mn}/\mu_{nn}$) and geometric mean gravity are *symmetrically* dependent on the search intensity parameter, $A_{mn}$.[28] Thus, all three formulations are appropriate modeling choices in empirical investigations on the role of search intensities on migration rates, once destination and sending location fixed effects are incorporated. Second, destination fixed effect of location $i$ embodies two separate terms, the origin fixed effect of location $i$, and a log status quo bias term. This motivates a methodology which uses the origin and destination fixed effects of the same location to back out the status quo bias term for each county $i$.

**Status Quo Bias**

To start, we note that each location $i = 1, ..., M$ in a migration gravity model appears both as a destination and as an origin. Thus, with a full set of sending location dummies and destination dummies, associated with each location are two estimated fixed effects, once as a sending location ($T_i$, $t_i$ and $\tau_i$), and once as a destination ($D_i$, $d_i$ and $\delta_i$). Using notations developed for outflow, inflow and geometric mean gravity where location dummies have expected utility interpretations, relative employment interpretations, and a combination of both respectively (18, 20, 21),

$$T_i - D_i = d_i - t_i = \tau_i - \delta_i = \ln(1+b_i). \tag{23}$$

[28]It should be noted that the expected utility and employment interpretations of outflow and inflow gravity coefficients, noted in (18) and (20) above, have analogous counterparts in the canonical structural migration gravity model without unemployment (e.g. Anderson, 2011).

Thus, the difference between the origin and destination fixed effects, when $m = n$, provides an estimate of the status quo bias of each location $i = 1, ..., M$.

By construction, $b_i$ is the expected utility premium that existing residents in $i$ attach to staying in $i$ ($W_i$) relative to a newcomer ($W_i/(1 + b_i)$). A positive $b_i$ naturally acts as a mobility barrier, and discourages labor movement both in and out of $i$. The distinction between status quo bias as opposed to search cost as a mobility barrier is that $b_i$ is origin-specific, whereas our search intensity characterization of mobility barriers, $a_{ij}$, is location pair-specific. The two can be combined to form a single parameter of status quo bias adjusted mobility barrier, as we have done in the definition of $\alpha_{ij} = a_{ij}(1 - \mathbb{I}_{ij} b_j/(1 + b_j))$ to parameterize the overall barrier to migration between $i$ and $j$. $\alpha_{ij}$, and hence outward gravity from $i$ to $j$ is decreasing in $b_j$.[29] Our task here is to separately tease out $b_i$ from $\alpha_{ij}$.

**The Role of Historical Status Quo Bias on Migration**

As shown in equation (23), status quo bias estimates are derived from the origin and destination fixed effects of the migration gravity regression for a given time period. It is therefore not possible to obtain unbiased estimates of their effect on migration in the same period due to endogeneity concerns arising from simultaneity. However, by estimating status quo biases for the same locations over time, we can construct historical status quo bias estimates, for example, a decade ago, as a proxy measure of current status quo bias. Naturally, for historical status quo bias estimates to be a good proxy of future status quo bias, there should be a strong and positive correlation between the past and future status quo biases. We now turn to our empirical application in which we ascertain the determinants of bilateral county population flows in three time periods. This offers an opportunity to verify the extent to which status quo bias estimates are indeed correlated over time at the county level, and accordingly whether persistence in these estimates may enable a more nuanced understanding of the contribution of place-based mobility inertias embodied in the status quo bias terms on migration.

[29] In relation to the literature, Grogger and Hanson (2011) in their analysis of international migration, for example, found that the bilateral migration cost implied by observed difference in income per capita across countries is very large. The implied bilateral migration cost can include any effects associated with status quo bias, as $\alpha_{ij}$ does.

**Table 1: Summary Statistics: Population Flow and Historical Search Frictions**

| | (1) All 2005-09 | (2) Large County Pairs 2005-09 | (3) Small County Pairs 2005-09 | (4) All 2015-19 | (5) Large County Pairs 2015-19 | (6) Small County Pairs 2015-19 |
|---|---|---|---|---|---|---|
| Outflow Ratio (per 1,000) | 0.675 | 0.275 | 1.270 | 0.560 | 0.248 | 0.978 |
| Inflow Ratio (per 1,000) | 0.683 | 0.304 | 1.209 | 0.560 | 0.268 | 0.917 |
| Geometric Mean (per 1,000) | 0.482 | 0.242 | 1.064 | 0.398 | 0.217 | 0.810 |
| Geog. Distance (1,000 miles) | 0.601 | 0.855 | 0.281 | 0.590 | 0.867 | 0.277 |
| Hist. Ethnic Distance | 0.714 | 0.830 | 0.495 | 0.696 | 0.832 | 0.467 |
| Hist. Ind. of Empl. Distance | 0.267 | 0.250 | 0.224 | 0.266 | 0.249 | 0.225 |
| Hist. Occ. Distance | 0.212 | 0.195 | 0.184 | 0.211 | 0.195 | 0.186 |
| Observations | 373,158 | 117,510 | 89,586 | 411,462 | 122,550 | 108,872 |
| Total County-to-County Flow | 17,439,207 | 10,595,408 | 2,070,822 | 17,636,966 | 11,031,790 | 2,011,775 |

Notes. 1. Outflow Ratio is defined as U.S. county level population flow per 1,000 origin non-movers (2005-2009, 2014-2018, 2015-2019 average, ACS) . 2. Inflow Ratio is defined as U.S. county level population flow per 1,000 destination non-movers (2005-2009, 2014-2018, 2015-2019 average, ACS). 3. The Geometric Mean refers to the geometric mean of the outflow and inflow ratios. 4. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic origin composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). 5. "Geog. Distance" refers to geographic distance (1,000 miles), and same-state status.

# 5 Data and Methodology

### Data

This study uses data on county-to-county population flows within the continental United States, obtained from the 2005–2009, 2014–2018, and 2015–2019 American Community Surveys.[30] The datasets contain yearly counts of individuals who have moved between counties as well as those who have stayed.

Following equations (17), (19) and (21), we compute the outflow ratio, the inflow ratio, and the geometric mean ratio as the share of the number of migrants from county $m$ to county $n$ in (i) the number of origin non-movers, (ii) the number of destination non-movers and (iii) the geometric mean of the number of origin non-movers and destination non-movers. Table 1 summarizes the decadal average change in these three county-to-county migration ratios. In columns 1 and 4 of Table 1, we look at the pooled sample of respectively $373,159$ and $411,462$ county pair observations covering 3,106 counties. As shown, all three migration ratios have fallen over time, indicating that despite improvements in internet communication and social media connections, internal migration within the United States has indeed slowed as alluded to in the introduction. Columns 2 and 5 display migration ratios between large origin and destination counties, defined here as counties with more than 50,000 workers in the labor force. Columns 3 and 6 display migration ratios between small counties, namely those with less than or equal to 50,000 workers – a cutoff that we will discuss in greater detail in the sequel – in the labor force. In 2015, 571 counties out of a total of 3,106 had a labor force greater than 50,000. As shown in Table 1, migration between this small number of large counties constitute the lion's share of internal migration flows in the United States (an annual total of 10.60 million out of 17.44 million in 2005-2009, and 11.03 million out of 17.64 million in 2015-19). [31]

Three different types of bilateral connections guide our measurement of bilateral search frictions. Specifically, we use historical (1940) county ethnic origin, occupation, and industry-of-employment compositions from the public Census microdata to construct historical ethnicity-based social and economic ties. Define a "distance" measure between sending county $m$ and

[30] We follow Eckert et al. (2020) to construct county crosswalk.

[31] Summary statistics comparing 2014-2018 and 2015-2019 is available in the appendix. Naturally, migration patterns in two consecutive time periods are very similar.

receiving county $n$ as

$$\sigma_\ell(m,n) = \sum_{k_\ell \in K_\ell} (s_{k_\ell m} - s_{k_\ell n})^2 \in (0,1), \quad \ell = eth, occ, ind \tag{24}$$

where $\ell$ is a member in a class of three search frictions controls, including U.S. historical (1940) ethnic origin ($eth$), occupation ($occ$), or industry-of-employment ($ind$). $K_\ell$ is the set of all available groups within search frictions control $\ell$ and $s_{k_\ell m}$ is the population share of a specific group $k_\ell$ in county $m$ in 1940. We use the 1940 sample because it is a full-count historical dataset providing detailed and complete coverage of county compositions across multiple dimensions.[32] By definition $\sigma_\ell(m,m) = 0 = \sigma_\ell(n,n)$.

Since our search frictions variables are based on historical county-level differences, it is instructive to visualize how these bilateral differences are related to migration flows, and to each other. Panels A-D in Figure A1 presents a binscatter plot of the relationship between bilateral outflow ratio ($\mu_{mn}/\mu_{mm}$) and geographic distance, historical ethnic composition distance, industry-of-employment composition distance and occupation composition distance respectively. In Panel A, outflow ratio decreases with geographic distance, as should be expected.

In Panel B, counties that are historically more ethnically distant continue to exhibit less mobility today (more than 70 years later). These relationships suggest that a history of prior ethnic networks can facilitate future migration flows as tighter social integration also fosters information flows and a lower cost of migration (e.g. Chau, 1997; Munshi, 2003). Since historical ethnic distance is arguably exogenous to current migration flows, we use historical ethnic distance as our first search frictions control.

Panels C and D show the other two search frictions indicators respectively based on historical industry-of-employment and occupation compositions. These county links are underemphasized in the literature as determinants of current population movements. The argument for using these proxies is that job search particularly for individuals with specific skills requires good fit, and such jobs may be more readily searchable in locations that are more similar in industry- / occupation-specific labor demand profiles (Kennan and Walker, 2011; Bryan and Morten, 2019). Panels C and

[32] Ethnic origin distance is based on birthplace. Persons born in the 50 U.S. states are assigned their states of birth. To eliminate small cells, non-U.S. birthplaces are categorized into larger regions: U.S. territories, Canada, Mexico, other North America, South America, Central America, Western Europe, Central/Eastern Europe, Southern Europe, Northern Europe, Russian empire, East Asia, Southeast Asia, Southwest Asia, Middle East, and Oceania. Persons born at sea or with an unidentifiable birthplace are excluded from the analysis. The occupation and industry-of-employment distance measures, in turn, are based on Census definition of major occupation groups and industry groups.

D in Figure A1 display binscatter plots of the raw data relationship between bilateral outflow ratio and historical industry-of-employment distance and historical occupation distance. A negative relationship is indicative of the tendency for historical economic links to continue to have an impact on today's mobility.

Since migrants balance both the benefits and the costs of migration, minimizing geographic distance, or each one of the three search frictions proxies need not be the optimal migration strategy. In Figure A2, we illustrate how migrants managed these tradeoffs by mapping the average distance and average search frictions experienced by migrants at the county level based on workers' chosen destination shares. In particular, in Panel A, we see that migrants from counties along the east and west coasts travel the farthest to their chosen destinations. Migrants from counties along the east and west coasts also tend to travel to locations with the greatest historical ethnic composition difference relative to the ethnic composition of their own counties. Indeed, origin-destination pairwise geographic distance and historical ethnic composition distance are positively correlated (correlation coefficient $= 0.36$). Panels C and D show the average industry of employment composition distance and the average occupation composition distance weighted by migrants' chosen destination shares. Here, we do not see the bi-coastal clustering evident in Panels A and B. Indeed, the correlation coefficient between origin and destination pairwise geographic distance and historical industry of employment (occupation) composition distance is very low at $0.056$ ($0.064$). But Panels C and D in Figures A1 and A2 are very similar, implying that historical industry of employment composition distance and occupation composition distance are quite highly correlated, with a correlation coefficient that is quite high at $0.898$.

Figures A1 and A2 together show that the bilateral geographic distance control is positively correlated with bilateral historical ethnic composition distance. By contrast, bilateral distance is uncorrelated with bilateral industry and occupation composition difference. These observations suggest that omitting historical ethnic composition distance can potentially introduce estimation bias on the geographic distance coefficient as geographic distance is relegated to take on the role that ethnic composition is supposed to play. Meanwhile, omitting historical industry and occupation composition distance can fail to control for important search frictions drivers of migration. With these observations in mind, we now turn to the estimation equations.

**Estimation**

There are three separate estimating equations, each using a different way of normalizing bilateral migration to yield a migration ratio. For outflow gravity, we estimate the following:[33]

$$\ln\left(\frac{\mu_{mn}}{\mu_{mm}}\right) = \ln A_{mn} - T_m + D_n + \varepsilon_{mn}, \tag{25}$$

and analogously for inflow gravity, we estimate:

$$\ln\left(\frac{\mu_{mn}}{\mu_{nn}}\right) = \ln A_{mn} + t_m - d_n + \epsilon_{mn}, \tag{26}$$

and finally, for geometric mean gravity:

$$\ln\left(\frac{\mu_{mn}}{\sqrt{\mu_{mm}\mu_{nn}}}\right) = \ln A_{mn} - \tau_m + \delta_n + \upsilon_{mn}. \tag{27}$$

The three equations differ only in their normalization, using respectively the log of non-movers in the origin, non-movers in the destination, and the geometric mean of the two. Because these differences are origin- and/or destination-specific, they affect only the origin and destination fixed effects and leave the estimated coefficients on the bilateral characteristics $A_{mn}$ unchanged. The pair of variables $D_n$ and $T_m$ in equation (25), $t_m$ and $d_n$ in (26) and $\tau_m$ and $\delta_n$ in (27) and are source and destination county fixed effects that absorb county-specific unobserved "push" and "pull" factors of migration, including mean county worker expected utility draws.

To unpack the determinants of the search intensity ratio $A_{mn}$, we assume that:

$$\ln A_{mn} = \ln\left(1 + \frac{a_{mn} - a_{mm}}{a_{mm}}\right) = \sum_{\ell = eth,occ,ind} \gamma_\ell \ln\left(1 + \sigma_\ell(m,n)\right) + \gamma_{dis} \ln dist_{mn} + B_{mn}, \tag{28}$$

where $\gamma_\ell$ and $\gamma_{dist}$ are the coefficients for search frictions controls and geographic distance. In particular, improvements in communication technologies and social media exchange can make it easier to maintain social ties, and the parameter, $\gamma_{eth}$, may increase to reflect these changes. More generally, better information technologies that make information about destinations easier to access can be incorporated through $B_{mn}$, the same-state fixed effect.

Equation (28) supposes that the search intensity deficit $(a_{mn} - a_{mm})/a_{mm}$ is a function of the historical search frictions controls $\sigma_\ell(m,n)$, in addition to geographical distance and same state status. $\varepsilon_{mn}$, $\epsilon_{mn}$ and $\upsilon_{mn}$ are functions of source-destination-specific shocks unrelated to search

[33] Recall from equation (17) that the ratio $\mu_{mn}/\mu_{mm}$ depends only on bilateral characteristics and are independent of the multilateral resistance term.

frictions or migration cost that affect migration.

By introducing search frictions proxies as controls, we extend the canonical migration gravity setup in which the log of distance is the primary variable that proxies for migration cost. If search frictions tend to be larger among county pairs that are farther apart, omitting search frictions as controls will bias and artificially inflate the distance elasticity estimate in absolute terms.

## 5.1 Discussion

**Search Frictions as a Driver of Migration**

Relocation motivations are heterogeneous and job search is one of many possible reasons (e.g. family reunification, education, starting a business, and retirement) why individuals migrate. For some of these reasons, search frictions are irrelevant particularly when the reason for moving is not job-related. If these search frictions controls are nonetheless included in the specification of the regression model, the precision of the origin and destination fixed effects we estimate will decrease, directly impacting the precision of our status quo bias estimates as well.

With county-level migration data, we looked for possible sources of migration motivation heterogeneity by ranking counties based on the size of the labor force. For origin and destination pairs with successively higher minimal labor force levels, we run outflow, inflow, and geometric mean regressions in equations (25) - (27) separately via ordinary least squares using geographic distance, a same-state dummy, and the historical search frictions measures as controls. Figure 1a plots the estimated coefficients of historical ethnic origin distance for county pairs with successively higher minimal labor force thresholds, starting from the full sample or zero labor force threshold.[34] Figure 1b plots the contribution of the three historical search frictions controls to the overall $R^2$ of the regression using Shapley value decomposition for successively higher minimum labor force thresholds starting from zero. These figures are based on outflow ratio regressions (2015-2019).[35]

From Figure 1a, we see that the coefficient estimate of ethnic origin distance is statistically significant and negative, as should be expected if ethnic origin distance is a mobility barrier – only for county pairs where origin and destination labor force exceed 50,000. The ethnic distance coefficient starts positive and near zero, but then decreases sharply and levels off at around -2.5 as the labor force threshold increases. In addition, from Figure 1b, the contribution of the three

[34] Table A1 reports results for the zero labor force threshold case (i.e. all counties).

[35] Results for the other time periods and from inflow ratio / geometric mean regressions show similar patterns.

search frictions controls as a group to the overall $R^2$ is very low for small county pairs. Their combined group contribution rises sharply and stabilizes to between 15% for county pairs with minimal labor force beyond 50,000. These findings suggest that search frictions controls are salient mostly for sufficiently large county pairs.

There are two potential reasons for the decline in the estimated importance of search friction controls in small counties. First, small counties tend to have more bilateral zero flows. Positive flows in these counties may mechanically select county pairs that are closer and more similar, compressing the observed variation in search-friction controls and attenuating their estimated coefficients. Second, labor markets in small counties are thinner, and the search-friction measures we include may not fully capture the relevant mechanisms. Networks that are likely important in thin labor markets but not captured by our controls include personal connections, a single dominant employer, or local word-of-mouth. In such cases, the origin and destination fixed effects in small-county regressions may absorb variation in search frictions that our controls miss, potentially inflating the implied status quo bias estimates.[36]

Rather than imposing the same search frictions coefficient estimate to all counties, and potentially introducing bias in status quo bias estimates, the main focus of our empirical analysis henceforth will be on county pairs with labor force greater than 50,000 based on the most recent 2015-2019 migration figures.[37]

**Extensive Margins**

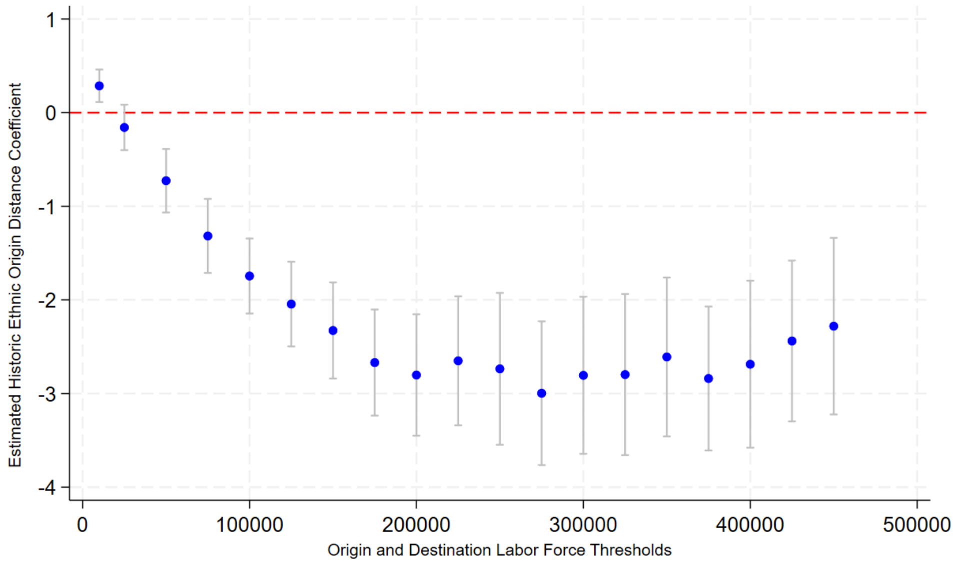
Some counties have many migration links, while for others there are fewer. In the full 2015-2019 sample, for example, the number of outward migration links ranged from 2 (Kennedy County TX) to 1,455 (Maricopa County AZ), out of a possible 3,105. Restricting to origins and destinations with more than 50,000 in labor force, the number of outward migration links ranged from 57 (Terrebonne Parish LA) to 543 (Maricopa County AZ) out of a maximum of 570. This feature is not uncommon in migration data (e.g. Beine et al., 2016). Two main empirical specifications to account for the extensive margin of migration have been adopted so far in the literature. These include a

[36] In Table A11), we estimate the status quo bias for small counties. The wider interquartile range of log status quo bias in small counties (0.831, Table A11) compared to large counties (0.772, Table 2) is consistent with alternative labor market networks in small counties interpretation.

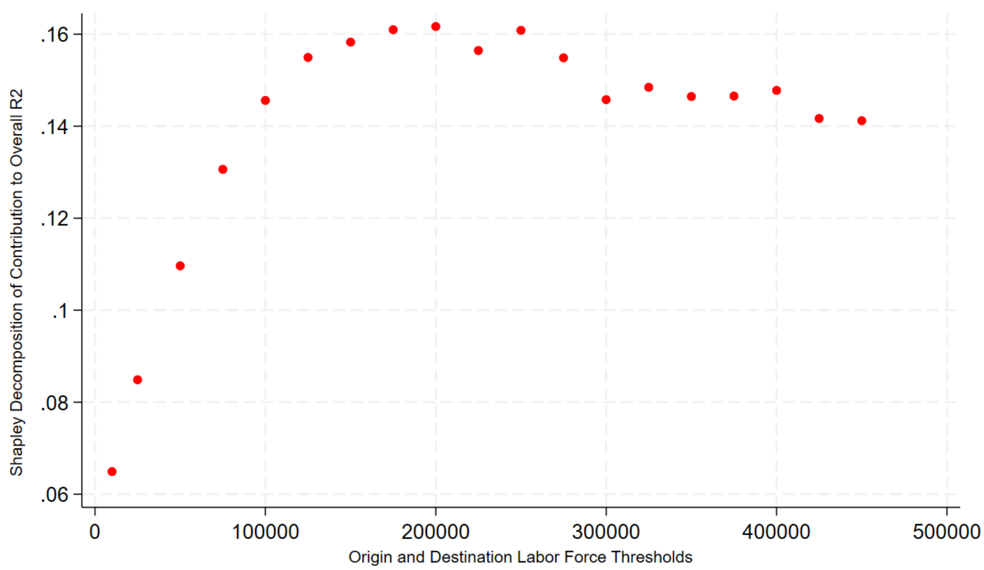
[37] Findings based on higher minimal labor force thresholds, e.g. 100,000, are very similar, though doing so reduces the number of counties by half. For completeness, in appendix tables A6 - A8 and A11 - A13, we report findings for county pairs with labor force greater than 100,000 and less than 50,000 respectively.

**Figure 1: Salience of Search Frictions Controls By Labor Force Thresholds**

**(a) Estimated Historic Ethnicity Distance Coefficients**




**(b) Shapley Decomposition of the Contribution of Search Frictions Controls**




Notes. 1.This figure displays the results of 2015-2019 outflow ratio regression in a sequence of subgroup analyses using increasing levels of minimal origin and destination labor force thresholds. 2. Each data point is the result of a separate regression. 3. The estimation includes origin and destination fixed effects, log geographic distance, same state dummy, and the full set of historical search frictions controls. 4. Standard errors are clustered at the origin and destination county levels. 5. The top graph displays the coefficient estimate and the confidence intervals associated with the historical ethnic origin distance control. 6. The bottom graphs shows the Shapley decomposition of the contribution of the historical search frictions (ethnic distance, industry of employment distance, and occupation distance) controls on the overall R2 of each regression. The Shapley decomposition includes 5 groups of variables, respectively, log geographic distance, same state dummy, historical search frictions controls, origin fixed effects and destination fixed effects.

two-step Heckman estimation requiring an instrument for the extensive margin selection equation. Another possibility is a count regression model via a Poisson pseudo maximum likelihood regression (Santos Silva and Tenreyro, 2021). In our case, while unobserved migration links may indeed be due to the true absence of migration, treating all unobserved links as zero migration in a selection equation will be inappropriate, since in many cases, migration may simply have been suppressed where there are just too few observations, rather than actual zeros. Meanwhile, a count regression approach does not work in our case either, since our main estimation equations present ratios of labor flows, rather than number of migrants.

Following recent migration gravity estimates in the United States such as Bailey et al. (2018), we focus on the intensive margin of migration.[38] The concern associated with ignoring unobserved flows (either because of the log of zeros with true zero migration flows, or missing /omitted observations) is that the influence of distance, networks, and other migration cost or search intensity related variables will be underestimated if the migration outcomes of the most remote / isolated locations are omitted. In our context, ignoring unobserved flows can mean that estimated destination fixed effects will be inflated, while origin fixed effects may be underestimated. Consequently, status quo bias – being the difference between origin and destination fixed effects from (23) – will likewise be underestimated. In what follows, we proceed with our intensive margin estimation with the important caveat that our estimated search intensity variables as well as status quo bias are lower bounds.

# 6 Results

In this section, we provide empirical estimates of the determinants of county-level bilateral migration and status quo bias, using regression specifications guided by the three applications of our model discussed above in Section 5.1.

## 6.1 Migration Gravity Estimates

The three columns of Table 2 report OLS estimates of the determinants of the outflow ratio respectively for 2005-2009, 2014-2018, and 2015-2019. Log geographic distance and a same state dummy, along with the three historical search frictions controls are included to control for county-pair level

[38]Notably, Eaton and Kortum (2002) in the context of the gravity of international trade takes a similar approach, where country fixed effects based on intensive margin trade gravity estimates, guided by the theory developed in Eaton and Kortum (2002), offers technological ranking interpretation.

differences in job arrival rates $A_{mn}$ in the outflow gravity equation (25). Robust standard errors clustered at the origin and destination county levels are included.

The results show that log distance and log outflow ratio are negatively correlated and the correlation is statistically significant at the 1% level, showing as may be expected that county-to-county migration is lower for counties that are farther apart geographically. A one percent increase in distance between counties decreases bilateral outflow ratio by 0.486% to 0.492%. These coefficient estimates are slightly lower (in absolute value) than the distance elasticity estimates in the literature, which range from around -0.7 to -0.8 in a study regarding the determinants of internal migration in New Zealand (Poot et al., 2016), to between -0.9 and -1.0 in a study on internal migration in the United States (Bailey et al., 2018). Another study uses decadal mobility data which yielded still larger estimates (-2.2 to -3.9) in absolute values (Eckert and Peters, 2022). None of these studies introduce search frictions controls. Inflation in the distance elasticity estimate of migration without search frictions controls is what one would expect if, as discussed in Section 5, distance between counties is positively correlated with search frictions controls such as historical ethnic composition, and industry-of employment composition. The same-state dummy is likewise statistically significant at the 1% level, reflecting a 0.706 to 0.815 log points increase in outflow ratio between county pairs in the same state, all else constant, than county pairs in different states.

The historical search frictions proxies reveal that ethnic and industry of employment based distance between counties are statistically significant obstacles to migration. The salience of historical ethnic origin distance on migration is consistent with prior studies that have consistently shown that there is path dependence in migration through social and ethnic networks (Munshi, 2014). The negative relationship between historical industry of employment differences and migration outflow ratio between counties holds even after controlling for same state status and geographic distance. This suggests that historical jobs-related economic linkages contributes to today's migration pattern. Between ethnic distance and industry of employment distance, ethnic distance has a larger impact on county-to-county migration ratios. Table 2 shows that after controlling for ethnic and industry of employment distance, occupational distance is not a salient driver of county-to-county migration, perhaps because industry of employment composition distance and occupation composition are so highly correlated as discussed in Section 5.

Complementing the results based on outflow ratios, Tables A2 and A3 display inflow ratio and geometric mean ratio gravity estimates. The coefficient estimates concur with Table 2.[39]

From these regressions, we retrieve the county-level origin and destination fixed effects. Being location fixed effects, we obtain normalized estimates for each county around a mean at zero. Thus for example, the origin fixed effect estimates of county $i$, $\widehat{T_i}$, should be interpreted as the log expected utility that residents attach to staying in county $i$ relative to what residents in the average county attach to staying put. Equivalently, $\widehat{T_i} = \ln W_i - (\sum_i \ln W_i)/M$. Likewise, destination fixed effect estimates are also normalized around zero: $\widehat{D_i} = \ln W_i/(1+b_i) - (\sum_i \ln W_i/(1+b_i))/M$.

Now if preferences do not harbor status quo bias, or $b_i = 0$ for all $i$, one would expect, from equations (3) and (4) that the origin and destination fixed effects of each county to be the same, or in other words $T_i = \ln W_i = D_i$ since $b_i = 0$. Thus, for every county $i$, we would expect:

$$\widehat{T_i} = \ln W_i - \ln(\sum_i \ln W_i)/M = \widehat{D_i}, \text{ if } b_i = 0\ \forall i.$$

This perfect correlation between $\widehat{T_i}$ and $\widehat{D_i}$ breaks down in the presence of status quo bias. Since the normalized fixed effects have zero means, we use the variance to summarize the divergence between $\widehat{T_i}$ and $\widehat{D_i}$ across counties. In particular,

$$var(\widehat{T}) = \frac{1}{M}\sum_i (\widehat{T_i})^2 = \frac{1}{M}\sum_i (\widehat{D_i})^2 = var(\widehat{D}) \text{ if } b_i = 0\ \forall i.$$

Origin and destination fixed effects are positively correlated but the correlation is not perfect, with the correlation coefficient at 0.510 in 2005-2009 and 0.502 in 2015-2019. Table 2 also displays the variance of the origin and destination fixed effects, showing an increase in the variance of the destination fixed effect over time while the variance of the origin fixed effect remain quite stable. By 2014-18 and 2015-19, destination fixed effects feature strictly higher variance than origin fixed effects, suggesting that individuals view the expected utility profiles of potential destination locations to be strictly more variable than how local residents assess the expected utility profiles of their own locations of origin.[40] With these observations in place, we now turn to leveraging

[39]Since the migration ratio variable in outflow ratio regression differ from inflow ratio and geometric mean regression only in how the base is specified (i.e. inflow regression replaces origin non-movers by destination non-movers and geometric mean regression replaces origin non-movers by the geometric of the origin and destination non-movers), the coefficient estimates of the three specifications should concur. The origin and destination fixed effects will differ naturally because of the change in the base of the migration ratios, and accordingly the variance of the origin and destination fixed effects differ from Table 2 as shown in Tables A2 and A3. However, since status quo bias is retrieved as the difference between the origin and destination fixed effects, status quo bias estimates are invariant to whether migration regression uses the outflow ratio, inflow ratio, or geometric mean.

[40]Theoretically, the variance of the origin fixed effects may be higher, equal, or lower than the destination fixed

**Table 2: Determinants of Population Outflow Ratios, Fixed Effects and Status Quo Bias Estimates**

| | (1)<br>Outflow 2005-09 | (2)<br>Outflow 2014-18 | (3)<br>Outflow 2015-19 |
|---|---|---|---|
| Log Geog. Distance (1,000 miles) | -0.486*** | -0.493*** | -0.492*** |
| | (0.011) | (0.012) | (0.012) |
| Same State Dummy | 0.707*** | 0.811*** | 0.815*** |
| | (0.079) | (0.089) | (0.091) |
| Log Hist. Eth. Distance | -0.725*** | -0.721*** | -0.727*** |
| | (0.153) | (0.172) | (0.173) |
| Log Hist. Ind. Distance | -0.579*** | -0.648*** | -0.606*** |
| | (0.155) | (0.174) | (0.163) |
| Log Hist. Occ. Distance | 0.254 | 0.094 | 0.124 |
| | (0.201) | (0.222) | (0.218) |
| Observations | 81111 | 86021 | 85196 |
| R2 | 0.549 | 0.511 | 0.509 |
| Variance Orig FE | 0.278 | 0.253 | 0.252 |
| Variance Dest FE | 0.192 | 0.259 | 0.262 |
| Max. log SQBIAS | 1.322 | 1.640 | 1.579 |
| Min. log SQBIAS | -1.611 | -1.772 | -1.791 |
| St Dev Ln SQBIAS | 0.494 | 0.518 | 0.509 |
| IQR Ln SQBIAS | 0.707 | 0.765 | 0.772 |

Notes. 1. This table displays the relationship between U.S. county level population outflow ratio (bilateral population outflow / total non-movers at source, 2005-2009, 2014-2018, 2015-2019 average, ACS) and search intensity controls. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23). Max. and Min. refer respectively to maximal and minimal estimates in the corresponding time period, and IQR is the interquartile range. 5. County-origin and county-destination fixed effects are included. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

origin and destination fixed effects to back out status quo bias estimates for each county.

### 6.2 Status Quo Bias Estimates

From equation (23), the log status quo bias term, $\ln(1+b_i)$, in county $i$ is given by the difference between the origin and destination fixed effects of county $i$, $T_i$ and $D_i$. Being the difference between estimated fixed effects, $\hat{T}_i$ and $\hat{D}_i$ each normalized to yield a zero mean, our estimate of the log status quo bias term :

$$\ln(1+\widehat{b_i}) = \widehat{T_i} - \widehat{D_i} \tag{29}$$

is also normalized with zero mean by construction. Thus, $\ln(1+\widehat{b_i})$ should be interpreted as the excess log status quo bias of county $i$ relative to the average county. Meanwhile, the double difference:

$$\left(\widehat{T_i} - \widehat{D_i}\right) - \left(\widehat{T_j} - \widehat{D_j}\right) = \ln(1+b_i) - \ln(1+b_j)$$

directly gives the difference in log status quo bias between two counties as the common population mean $\ln(\sum_i \ln W_i)/M$ is differenced out.

To interpret the results in Table 2, we note that the top log status quo bias is 1.322 (Richmond County NY) in 2005-2009. This implies that residents of Richmond county harbor a utility premium of staying in the county over newcomers $(1+b_i = exp(1.322) =)$ 3.75 times higher than the utility premium residents in the average county attach to staying put over new residents. During the same time period, a one standard deviation increase in log status quo bias (0.494) has the same migration effect as a reduction in expected utility ratio ($W_n/W_m$) between a destination-origin county pair by 38.98% ($= exp(-0.494) - 1$).[41] By 2015-2019, this percentage reduction has increased slightly to 39.83% ($= exp(-0.508) - 1$).

#### Status Quo Bias Equivalents

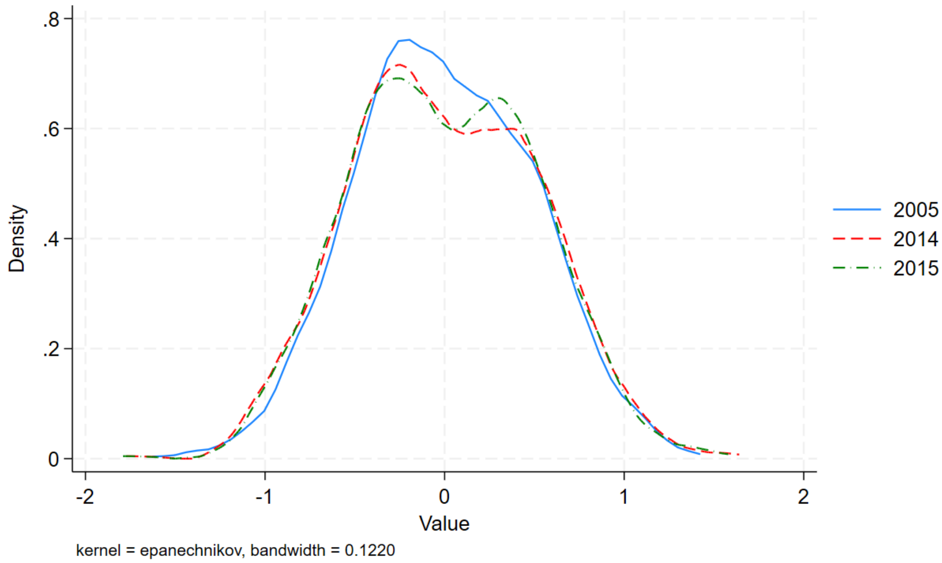
In addition to expected utility effects, we can also express status quo bias differences in terms of their spatial equivalents using the results in Table 2. In 2005-2009, a one standard deviation increase in log status quo bias $(0.494)$ has the same outflow ratio effect as increasing distance

effect. The empirical correlation between the status quo bias and origin fixed effects will determine which one applies.

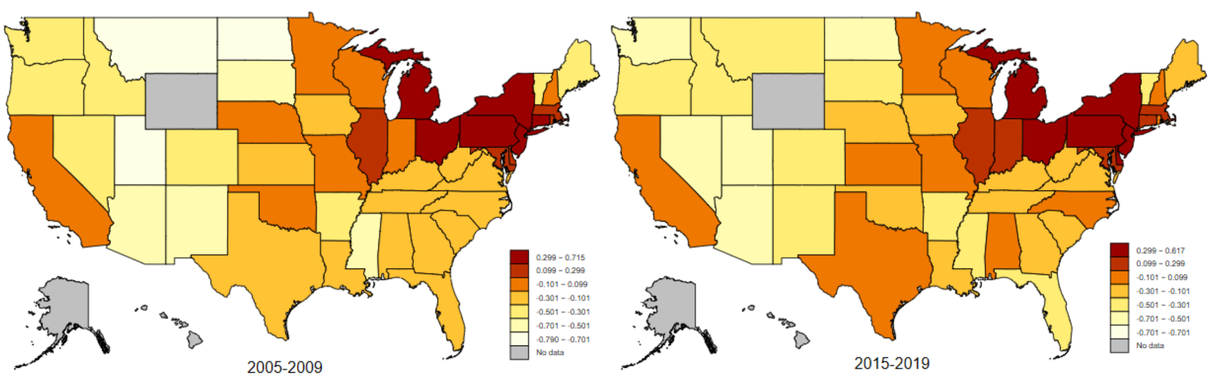
[41] This follows from equation (18), where origin and destination fixed effects in outflow gravity regressions have log origin and destination expected utilities interpretation adjusted for status quo bias: $\ln \mu_{mn} - \ln \mu_{mm} = \ln A_{mn} - T_m + D_n$ and ($T_m = \ln W_m$ and $D_n = \ln W_n/(1+b_n)$). Thus, an increase in log status quo bias by 0.494 log points has the same migration ratio effect as a reduction in expected utility ratio $W_n/W_m$ by 38.98% ($= exp(-0.494) - 1$).

**Figure 2: Status Quo Bias Dispersion**

**(a) Kernel Density Estimates Over Time**




**(b) State-Level Map of the State-Level Log Status Quo Bias Averages**




Notes. 1. This figure shows the dispersion of status quo bias estimates across time and space. 2. The top figure shows the kernel density plots of the log status quo bias estimates in the three time periods. 3. The bottom figure displays a state-level map of the log status quo bias averages in the United States respectively in 2005-2009 and 2015-2019. 4. The status quo bias estimates are derived from outflow ratio regression in Table 2. 5. The two states outside of the continental United States (Alaska and Hawaii) were not included in the analysis. Wyoming was dropped due to small county-level labor force.

between origin and destination county pairs by a factor of 1.76 $(= exp(0.494/0.486) - 1)$, or 1,135.7 $(1.76 \times 645.3)$ miles evaluated at median destination-origin county distance (645.3 miles). In 2014-2018 and 2015-2019, a one standard deviation increase in log status quo bias is equivalent to an increase in distance by a factor of 1.85 $(= exp(0.517/0.493) - 1)$ and 1.81 $(= exp(0.508/0.492) - 1)$ respectively.

The salience of status quo bias is also evident in relation to state borders. Border effects capture additional migration adjustment costs arising from differences for example in taxes, local government policies, and public service access. From Table 2, the estimated same-state coefficient for 2005–2009 is 0.707. This magnitude is equal to the interquartile range of log status quo bias during the same period. Thus, moving from the 25th to the 75th percentile of log status quo bias has the same effect on the migration ratio, all else equal, as migrating out of state rather than within state. Such a change reduces the outflow ratio by 50.7% $(|\exp(-0.707) - 1|)$ relative to an otherwise identical county pair in the same state. In 2014–2018 and 2015–2019, the interquartile range effects of log status quo bias remain similar to, but slightly smaller than, the same-state coefficients, suggesting that status quo bias continues to have a level of impact comparable to a cross-state migration effect.

The dispersion in status quo bias has a spatial dimension as well. To see this, we aggregate county-level log status quo bias estimates from Table 2 to the state-level and map the resulting average state-level pattern in Figure 2b. As shown, status quo bias estimates are highest in Pennsylvania, New Jersey, New York and the Rust Belt states – states that contain large metropolitan urban job centers. States showing the lowest status quo bias are Arizona, Utah, Washington, Nevada, and North Dakota.

**Persistence and Migration Dynamics**

Because we estimate status quo bias at the county level for three periods, we can assess the stability of these estimates over time to reveal whether county-level forces generating location-history dependence show persistence. Figure 3 plots the relationship between county-level log status quo bias estimates across periods: year-to-year (2014–2018 to 2015–2019) with several years of overlap, and decade-to-decade (2005–2009 to 2015–2019) with no overlapping years. The estimates exhibit strong positive correlation, with correlation coefficients of 0.983 for 2014–2018 to 2015–2019 and 0.890 for 2005–2009 to 2015–2019.

To what extent can the decline in migration shares over time, as documented in Table 1, be attributed to changes in status quo bias?[42] Using observations from three periods ($t_0 = 2005–2009$, $t_1 = 2014–2018$, and $t_2 = 2015–2019$), we define the change in log outflow ratios between 2005–2009 and 2015–2019 as

$$\Delta^2 ln(\mu_{mn}/\mu_{mm}) \equiv \ln(\mu_{mn}^{t_2}/\mu_{mm}^{t_2}) - \ln(\mu_{mn}^{t_0}/\mu_{mm}^{t_0})$$

and examine its correlation with the lagged change in log status quo bias estimates from 2005-2009 to 2014-2018:

$$\Delta^1 ln(1+\widehat{b_n}) \equiv \ln(1+\widehat{b}_n^{t_1}) - \ln(1+\widehat{b}_n^{t_0}).$$

We estimate the following OLS regression:

$$\Delta^2 \ln \mu_{mn}/\mu_{mm} = \beta_o + \beta_b \Delta^1 \ln 1(+\widehat{b_n}) + \beta_n \Delta^1 \ln W_n + \beta_m \Delta^1 \ln W_m + \ln A'_{mn} + \zeta_{mn}. \tag{30}$$

where $\Delta^1 \ln W_n = \hat{T}_n^{t_1} - \hat{T}_n^{t_0}$ and $\Delta^1 \ln W_m = \hat{T}_m^{t_1} - \hat{T}_m^{t_0}$ denote the lagged changes in expected utility for locations $n$ and $m$ over the period defined in equation (18) above.[43] The full set of distance and historical search-friction controls is included to allow migration-share growth to vary with geography and search frictions:

$$\ln A'_{mn} = \sum_{\ell=eth,occ,ind} \gamma'_\ell \ln(1+\sigma_\ell(m,n)) + \gamma'_{dis} \ln dist_{mn} + B'_{mn}, .$$

Finally, $\zeta_{mn}$ is the error term. Standard errors are clustered at the origin and destination county levels.

Table 3 presents the results. The lagged change in log status quo bias is negatively and significantly correlated with changes in the log outflow ratio. Specifically, a one standard deviation increase in the change in status quo bias (0.230) between 2005 and 2014 is associated with an 16.8% decline in the decadal change in outflow ratio from 2005 to 2015 ($= \exp(-0.799 \times 0.230) - 1$). Increases in the expected utility proxies in the origin and destination counties reflect the expected push and pull effects on the outflow ratio.[44]

[42]We thank an anonymous referee for suggesting that we examine the role of status quo bias in migration dynamics.

[43]Both the log status quo bias estimates and origin fixed effects are normalized relative to the average county. County-specific estimates differ from actual values by a constant in a given period. These constants are absorbed in the regression intercept and do not affect the coefficient estimates.

[44]Note that if nothing else (e.g., coefficients associated with geography and search frictions) changed during this decade, equation (18) predicts that $-\beta_b = \beta_n = -\beta_m = 1$. Table 3 shows that these coefficients are indeed close to one in absolute value, although the importance of geography and search frictions has evidently shifted over time. In particular, growth in outflow ratio is higher among counties that are closer together or within the same state. Conversely, counties

**The Contribution of Historical Status Quo Bias to Migration Patterns**

Another way to assess the contribution of status quo bias to migration patterns is to examine the contribution to $R^2$ when it is included as a regressor. Since status quo bias estimates are derived from observed migration flows using gravity regressions, including contemporaneous status quo bias as a control would introduce simultaneity bias and potentially overstate its contribution.

To overcome this simultaneity concern, we turn to an examination of the extent to which *historical* levels of status quo biases contribute to bilateral migration flows in subsequent periods. Our objective is to assess the extent to which persistent place-specific factors embodied in our status quo bias estimates may have affected internal migration flows within the United States.

Thus, we re-estimate the outflow-ratio, inflow-ratio and geometric mean gravity regression from all county $m$ to $n$ pairings for two five year periods 2014-2018 and 2015-2019, using the standard distance and same state dummies, as well as historical search frictions proxies. In addition to this list, we replace the canonical origin fixed effect by historical origin fixed effect estimates of county $m$ from 2005-2009, $\widehat{T_m}$. Since the destination fixed effect of county $n$ is by definition given by the origin fixed effect of county $n$, $T_n$ minus the log status quo bias in county $n$, $\ln(1 + b_n)$ from equation (23), we replace the canonical destination fixed effect in the migration gravity regressions by separately introducing the historical (2005-2009) origin fixed effect estimate for county $n$, $\widehat{T_n}$ as the counterfactual destination effect if there were no status quo bias, and the log status quo bias estimate for county $n$, $\ln(1 + \widehat{b_n})$ from 2005-2009.

Table 4 displays results of the gravity regressions, and Table 5 shows the Shapley value decomposition of the overall $R^2$ of each regression. The results in Table 4 show that the historical log status quo bias proxies are statistically significant at the 1% level and negatively correlated with the three migration ratios. The coefficients are close to negative unity, which is what our theory would predict to hold.

In the Shapley value table (Table 5), we consider 6 groups of variables, including geographic distance, same state, historical search frictions proxies (including ethnic, industry-of-employment and occupation distance), origin fixed effect, destination fixed effect, and historical log status quo bias. From the Shapley decomposition results in Table 5, we find that historical (2005-2009) status quo bias estimates account for 4.84% to 7.74% of the $R^2$ from the migration gravity regressions for

with larger historical occupation distance experienced slower growth in migration shares, all else equal.

**Table 3: Changes in Status Quo Bias on Migration Dynamics**

| | (1)<br>Change in Log Outflow Ratio (2005-2009 to 2015-2019) |
|---|---|
| Lagged Change in Ln Status Quo Bias (2005-2014, Outflow) | -0.799*** |
| | (0.034) |
| Lagged Change in Ln W_n (2005-2014) | 0.694*** |
| | (0.055) |
| Lagged Change in Ln W_m (2005-2014) | -0.887*** |
| | (0.044) |
| Ln Geog. Distance (1,000 miles) | -0.012** |
| | (0.006) |
| Same State Dummy | 0.126*** |
| | (0.030) |
| Ln Std. Hist. Eth. Distance | -0.012 |
| | (0.049) |
| Ln Std. Hist. Ind. Distance | 0.140 |
| | (0.125) |
| Ln Std. Occ. Distance | -0.364** |
| | (0.159) |
| Observations | 47241 |
| Std. Dev. Lagged Change in Ln SQBIAS | 0.230 |
| Std. Dev. Lagged Change in Ln W_m | 0.138 |
| Std. Dev. Lagged Change in Ln W_n | 0.138 |

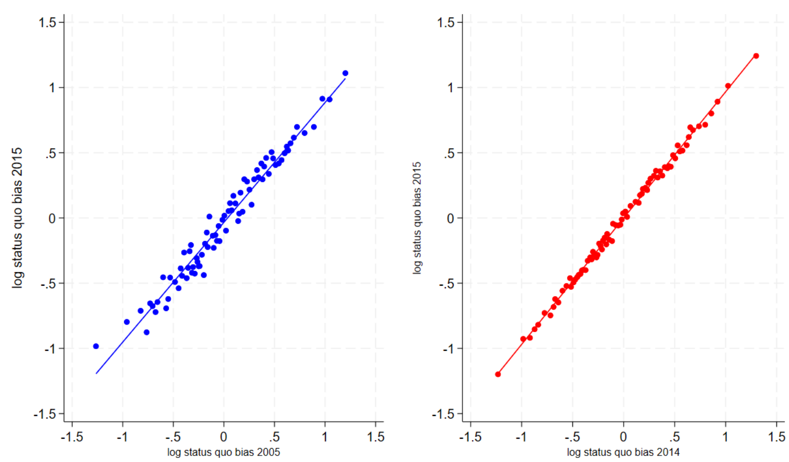
Notes. 1. This table shows how lagged changes in destination-county log status quo bias between 2005–2009 and 2014–2018 affect changes in the log bilateral outflow ratio between 2005–2009 and 2015–2019.. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23) using results in Table 2. 5. Lagged changes in log expected utilities are proxied by origin fixed effects from the outflow regressions in columns 1 and 2 in Table 2. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2014-2018 and 2015-2019. To put these Shapley value results in context, we calculate the relative importance of the distance (24.51% to 41.51%) and status quo bias (5.25% to 11.38%) on migration ratios. Across specifications, status quo bias accounts for 13-45% of distance's explanatory contribution.[45]

Since historical controls are arguably noisy proxies for current day conditions, the resulting status quo bias coefficient will be biased towards zero (Angrist and Pischke, 2009). Such attenuation biases can artificially deflate the Shapley value $R^2$ contribution of the status quo bias variable downwards. Thus, the Shapley value contribution of the status quo bias variable in Table 5 should be seen as a lower bound.

The main takeaways from these applications are that introducing status quo bias in migration gravity modelling (i) helps rationalize why origin and destination fixed effects are systematically different over time, (ii) provides an additional reason as to why county-to-county migration has been low despite interregional differences in job opportunities and expected utilities, and furthermore (iii) allows for an evaluation of the extent to which status quo bias may have contributed to differences in migration ratios between different county pairs, as well as to the overall $R^2$ of migration gravity regressions.

**Figure 3: Status Quo Bias Estimates Over Time**




Notes. 1.This figure displays binscatter plots of log status quo bias from 2005-2009 to 2015-2019 (Table 2), and from 2014-2018 to 2015-2019 respectively.

[45]These are obtained by taking the ratio of the Shapley decomposition share associated with status quo bias and the corresponding Shapley decomposition share associated with distance. For 2015-19, status quo bias' contribution shares are 30.5 (=7.61/24.98)%, 42.5%, 12.6% for outflow ratio, inflow ratio and geometric mean regressions. For 2014-18, status quo bias' contribution shares are 31.6%, 45.1% and 13.2% respectively for outflow ratio, inflow ratio and geometric mean regressions.

**Table 4: Determinants of Population Flow Ratios with Historic Fixed Effects and Status Quo Bias Estimates**

| | (1)<br>Outflow<br>2015-19 | (2)<br>Inflow<br>2015-19 | (3)<br>Geometric Mean<br>2015-19 | (4)<br>Outflow<br>2014-18 | (5)<br>Inflow<br>2014-18 | (6)<br>Geometric Mean<br>2014-18 |
|---|---|---|---|---|---|---|
| Log Geog. Distance (1,000 miles) | -0.575*** | -0.580*** | -0.524*** | -0.568*** | -0.577*** | -0.519*** |
| | (0.011) | (0.011) | (0.009) | (0.011) | (0.012) | (0.009) |
| Same State Dummy | 0.681*** | 0.716*** | 0.560*** | 0.673*** | 0.716*** | 0.558*** |
| | (0.057) | (0.060) | (0.059) | (0.056) | (0.058) | (0.058) |
| Log Std. Hist. Eth. Distance | -0.922*** | -0.855*** | -1.159*** | -0.940*** | -0.860*** | -1.166*** |
| | (0.088) | (0.092) | (0.098) | (0.085) | (0.088) | (0.095) |
| Log Std. Hist. Ind. Distance | -0.401** | -0.355** | -0.557*** | -0.436** | -0.385** | -0.585*** |
| | (0.169) | (0.177) | (0.176) | (0.171) | (0.181) | (0.177) |
| Log Std. Occ. Distance | -0.279 | -0.326 | -0.216 | -0.313 | -0.367* | -0.265 |
| | (0.205) | (0.219) | (0.208) | (0.202) | (0.216) | (0.204) |
| Hist. Origin FE (2005, Outflow) | 0.812*** | | | 0.820*** | | |
| | (0.021) | | | (0.021) | | |
| Hist. Dest. FE, Adj. (2005, Outflow) | 1.215*** | | | 1.213*** | | |
| | (0.030) | | | (0.030) | | |
| Hist. Log Status Quo Bias (2005, Outflow) | -1.219*** | | | -1.220*** | | |
| | (0.031) | | | (0.030) | | |
| Hist. Origin FE (2005, Inflow) | | 1.200*** | | | 1.206*** | |
| | | (0.029) | | | (0.029) | |
| Hist. Dest. FE, Adj. (2005, Inflow) | | 0.769*** | | | 0.763*** | |
| | | (0.031) | | | (0.033) | |
| Hist. Log Status Quo Bias (2005, Inflow) | | -0.941*** | | | -0.956*** | |
| | | (0.023) | | | (0.022) | |
| Hist. Origin FE (2005, Geo.) | | | 0.801*** | | | 0.834*** |
| | | | (0.050) | | | (0.051) |
| Hist. Dest. FE, Adj. (2005, Geo.) | | | 0.719*** | | | 0.682*** |
| | | | (0.123) | | | (0.126) |
| Hist. Log Status Quo Bias (2005, Geo.) | | | -0.894*** | | | -0.889*** |
| | | | (0.049) | | | (0.050) |
| Observations | 59162 | 59162 | 59162 | 59657 | 59657 | 59657 |
| R2 | 0.534 | 0.533 | 0.411 | 0.535 | 0.535 | 0.411 |

Notes. 1. This table displays the determinants of U.S. county level population outflow ratio, inflow ratio and geometric mean ratio. 2. This table differs from Tables 2, A2 and A3 in that origin fixed effects are replaced by estimated origin fixed effects from 2005. 5. Adjusted historical destination fixed effect are the counterfactual destination fixed effects if there were no status quo bias, or the historical origin fixed effect of the corresponding county. 6. Historical status quo bias are the log status quo bias estimates from 2005. 8. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: **Shapley Decomposition with Historical Fixed Effects and Status Quo Bias Estimates**

| | Outflow 2015-19 (%) | Inflow 2015-19 (%) | Geometric Mean 2015-19 (%) | Outflow 2014-18 (%) | Inflow 2014-18 (%) | Geometric Mean 2014-18 (%) |
|---|---|---|---|---|---|---|
| Log Geog. Distance | 24.98 | 25.64 | 41.59 | 24.51 | 25.21 | 41.04 |
| Same State Dummy | 16.5 | 16.14 | 27.09 | 16.39 | 16.05 | 27.02 |
| Hist. Search Frictions Controls | 13.35 | 12.84 | 21.49 | 13.35 | 12.86 | 21.58 |
| Hist. Origin FE (2005, Outflow) | 24.5 | 16.06 | 2.27 | 24.88 | 16.29 | 2.5 |
| Hist. Dest. FE. Adj. (2005, Outflow) | 13.05 | 18.42 | 2.31 | 13.14 | 18.22 | 2.44 |
| Hist. Log Status Quo Bias (2005, Outflow) | 7.61 | 10.89 | 5.25 | 7.74 | 11.38 | 5.42 |

Notes. 1. This table presents the Shapley decomposition of the overall R2 of the six regressions in Table 4. 2. Six groups of control variables are used, including log geographic distance, the same state dummy, the three historical search frictions controls, historical origin fixed effects, historical destination fixed effects adjusted to reflect the counterfactual scenario where there is no status quo bias, and finally, the historical status quo bias estimate. 3. The historical fixed effects and status quo bias estimates are taken from the 2005 migration gravity regressions in Table 2, A2 and A3.

# 7 Validation

In this section, we validate several claims made in the paper: (i) historical search friction measures serve as meaningful proxies for future information flows between counties; (ii) status quo bias estimates are associated with place-based factors that shape how residents' expected utility for a location differs from that of newcomers; and (iii) origin fixed effects from outflow and inflow regressions provide meaningful estimates of expected utility and relative employment levels, respectively.

**Mechanism of Historic Links on Current Mobility**

What exactly do the three search frictions proxies measure? While micro-level studies confirming the importance of job referrals and professional networks on job search abound (e.g. Belot et al. (2018) and Gautier et al. (2018)), it would be helpful to more directly ascertain the mechanism linking our historical search frictions proxies with the strength of informational connections between individuals living in different counties. Thus, to validate the mechanism that connect historical search frictions proxies with migration propensities, we use county-to-county data on social media connections. The Social Connectedness Index (SCI) from Bailey et al. (2018) gauges the intensity of bilateral friendship networks.[46] The SCI is constructed using the total number of Facebook friendship links between individuals located in a pair of counties: for every county pair $m$ and $n$

$$SCI_{mn} = \frac{\text{Facebook Connections}_{mn}}{\text{Pop}_m \text{Pop}_n}, \tag{31}$$

where Facebook Connections is the number of Facebook friendship links and $Pop_m$ and $Pop_n$ denote the corresponding county population.[47] Bailey et al. (2018) normalizes the index such that the maximum value is 1,000,000 (Los Angeles, CA). The SCI has increasingly been used as a benchmark for the intensity of information flow and opinion exchanges between US counties (Bailey et al., 2018, 2020). To our knowledge, with its 239 million users, the SCI is the only dataset that provides a comprehensive coverage of friendship networks at the national level in the United States. Figure A3 plots counties' average social connectedness. As shown, there is a great deal of variations in the level of average social connectedness by county in the US, featuring dense

[46] The SCI provides a snapshot of the universe of all active Facebook friendship links in April 2016. A Facebook friendship is taken to be active if users have interacted in the 30 days before the April 2016 snapshot.

[47] This variable is different from the one used in Bailey et al. (2018), where friendship links are adjusted by the number of Facebook users instead of by county population.

friendship networks on the U.S. coasts but also parts in the Midwest and the South.

Consider an OLS regression of county-pair SCI to examine how current county-to-county social media connections are correlated with our historical search frictions proxy, geographic distance, and same-state status. A strong correlation would suggest that historical ties – such as those based on ethnic similarity or industry-of-employment similarity – persist over time and may continue to facilitate information flows through present-day connections between counties. Table 6 summarizes the results. As shown, current opportunities for information exchange through social media connections are influenced by historical links in ethnicity and industry of employment. These relationships are negative and statistically significant. Historical occupational links, however, have effects close to zero – similar to what we observed in the migration regressions. Also consistent with the migration results, ethnic ties play a stronger role than industry-of-employment distance. Together, historical search frictions proxies complement geographic distance and same-state status in providing a more complete picture of the factors driving the intensity of information exchange between county pairs.

**Table 6: The Facebook Social Connectedness Index and Historical Search Frictions Proxies**

| | (1)<br>Log Social Connectedness Index |
|---|---|
| Log Geog. Distance (1,000 miles) | -0.452*** |
| | (0.034) |
| Same State Dummy | -1.186*** |
| | (0.165) |
| Log Std. Hist. Eth. Distance | -4.464*** |
| | (0.344) |
| Log Std. Hist. Ind. Distance | -1.993*** |
| | (0.525) |
| Log Std. Hist. Occ. Distance | 0.420 |
| | (0.614) |
| Observations | 85196 |
| R2 | 0.303 |

Notes. 1. This table displays the relationship between the Facebook Social Connectedness Index and search intensity controls among county pairs with positive migration flows as in Table 2, A2 and A3. 2. The three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic origin composition distance, historical industry-of-employment composition distance, and occupation composition distance. "Geog. Distance", and "Same State Dummy" refers to geographic distance (1000 miles), and same-state status. 3. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**The Place-Based Origins of Status Quo Bias**

Since status quo bias contrasts expected utility assessments between individuals with first-hand exposure to a location through lived experiences relative to newcomers, one would expect that the extent of the bias should be correlated with demographics such as age and family factors, workers' skill level that can dictate the opportunity cost of immobility, and community-level cohesiveness considerations. In particular, some examples include (i) stage of life considerations – since age endows an individual with time to add value to assets, invest in local friendship networks and act on locational preference such as climate (e.g. Sjaastad (1962); Molloy et al. (2014)), and (ii) community ties of shared beliefs and preferences – since migration would require individuals to forgo direct day-to-day contact with longstanding communities of individuals who share similar religious beliefs and local political preferences (Zanfrini, 2020; Acemoglu et al., 2013).

We collect a wide array of standardized county-level contemporaneous correlates from the ACS, including crime rates, religiosity, demographics, family structure, the environment, and housing attributes.[48] To unpack the interpretation of the estimated status quo bias, we employ a Least Absolute Shrinkage and Selection Operator (LASSO) to identify significant correlates of our estimates of status quo bias. Table 7 reports the significant correlates of status quo bias estimates selected by LASSO based on outflow gravity estimates for 2015-2019.[49] We use a cross-validation method and select the shrinkage parameter according to minimum Bayesian information criterion.

Using this approach, we confirm that our estimates of status quo bias reflect the importance of community-level commuting, housing, climate, religiosity, political leanings, and demographics. In particular, status quo bias is highly positively correlated with county-level congestion forces such as commute time. This is consistent with asymmetric perceptions about the costs associated with congestion forces, where for example existing residents have had the time to find ways to cope with the disutility of congestion but new residents have yet to do so.

The role of housing features prominently as a correlate of status quo bias. In particular, the higher (lower) the share of older houses, the higher (lower) the status quo bias in the county. This observation gets directly at the heart of asymmetric preferences due to first-hand exposure through lived experiences. Sunk investment in housing makes relocation difficult, and thus status quo bias high, because of the high expected cost required to acquire a new house in a new neighborhood equipped with compensating quality improvements that may have taken years to take

[48] See Table A4 for a complete list of the variables.

[49] Table A5 in the appendix shows the full list of LASSO select covariates.

root before the move.

Relatedly, we also find status quo bias to be positively correlated with places with warmer climate extremes. This may be suggestive of the need for climate adaptation investments as another form of sunk costs (e.g. investments in resilient housing) that are not readily transferable to a different location. People may also have asymmetric understanding about the physical and mental load impacts of warmer climates until they have had experience living in such conditions.

Local communities can bring together people with similar beliefs and outlooks. The decision to move away from a place thus entails separation from familiar networks of people who share similar beliefs (Zanfrini, 2020; Acemoglu et al., 2013). Consistent with these local community-based network considerations, the LASSO estimates suggest that counties with higher shares of individuals adhering to major religions in the United States (e.g. Mainline Protestant, and United Methodist Church) tend to exhibit higher status quo biases. Large concentrations of adherents to these religious groups can be found both in urban centers as well as in counties far away from cities, and as such this LASSO association may not be simply attributed to residential clustering of adherents of religious groups in select urban locations (Association of Statisticians of American Religious Bodies, 2020).[50] In addition to religion, counties with higher shares of Republican votes also exhibit higher status quo bias, suggesting that migration decisions are affected by whether workers live in communities where more people share similar political beliefs.

Finally, demographics also play an important role. Counties with a higher share of dependents – both young (% with children) and old (% aged older than 54) – tend to have residents who are more attached to their current surroundings as jobs-based motivation for moving is arguably weaker for these individuals. By contrast, working-age individuals, particularly those with higher education, are generally more mobile as the payoffs associated with the highest returns on their human capital are more likely to outweigh moving costs. Consequently, counties with a larger share of dependents and / or a smaller share of working-age or highly educated residents tend to exhibit higher county-level status quo bias.

These findings serve as a useful reminder that spatial heterogeneity in living standards extends well beyond wage considerations and job opportunities. The correlates of our status quo bias estimates include demographic profiles, community-level religiosity and political character-

[50]By contrast, some religious groups cluster in locations far away from major metropolitan cities and economic hubs (e.g. Lutheran Church – Missouri Synod, Latter-day Saints, Southern Baptist Convention), the negative association between the share of adherents to these religious groups and status quo bias may reflect other attributes of their locational clusters (e.g. distance from major job hubs) as opposed to religion itself as a contributor to status quo bias.

istics, congestion, and climate. Naturally, different population subgroups – by skill level, gender, or birthplace – may value these features differently, and additional factors may also influence status quo bias in locational preferences. Future work can engage with more disaggregated estimates of status quo bias at the population sub-group level to verify the salience of these status quo bias correlates across population subgroups.

**Interpreting Origin Fixed Effects**

From the outflow ratio equation in (17), the origin fixed effect is supposed to reflect the expected utility assessment residents hold about their own counties. Since these expected utility levels provide an overall assessment summarizing the role of jobs, wages and local amenities – the latter is particularly challenging to capture and often unobservable to a researcher – the estimated origin fixed effects allow for a ranking of counties summarizing the joint contribution of both observable and unobservable local characteristics that individuals care about in migration decisions.

Table 8 lists the top 20 counties with the highest origin fixed effects estimates based on outflow regressions for the three time periods. These counties are home to major economic hubs, large metropolitan centers with high population density and well-developed public infrastructure. These locations are naturally culturally diverse attracting high percentages of foreign-born population. In particular, the average foreign-born population share in these top 20 counties is 23.74% in 2015-2019, compared to 9.25% in the rest of the counties.

Origin fixed effects from inflow ratio regressions, by contrast, reflect employment levels from equation (19). In particular, $T_i$ reflects the general equilibrium term $(1-u_i)/\ln(u_i)$.[51] We use ACS estimates of county-level unemployment rate $U_i$, to construct a proxy for the term $(1-u_i)/\ln(u_i)$ in each county $i$.[52] Figure 4 plots the relationship between the estimated inflow ratio regression origin fixed effect and the ratio $(1-U_i)/\ln(U_i)$ for 2015-2019. Consistent with theory, we find a positive relationship between the origin effect estimates and the employment ratio $(1-U_i)/\ln(U_i)$.

[51]Note that the unemployment rate here $u_i$ is defined as the share of individuals residing in county $i$ that searched for a job but did not find one relative to the total number of job seekers in the county (inclusive of individuals who left the county as a result of a successful job search leading to out-migration, but not including individuals who migrated into the county as a result of job search originating from other counties).

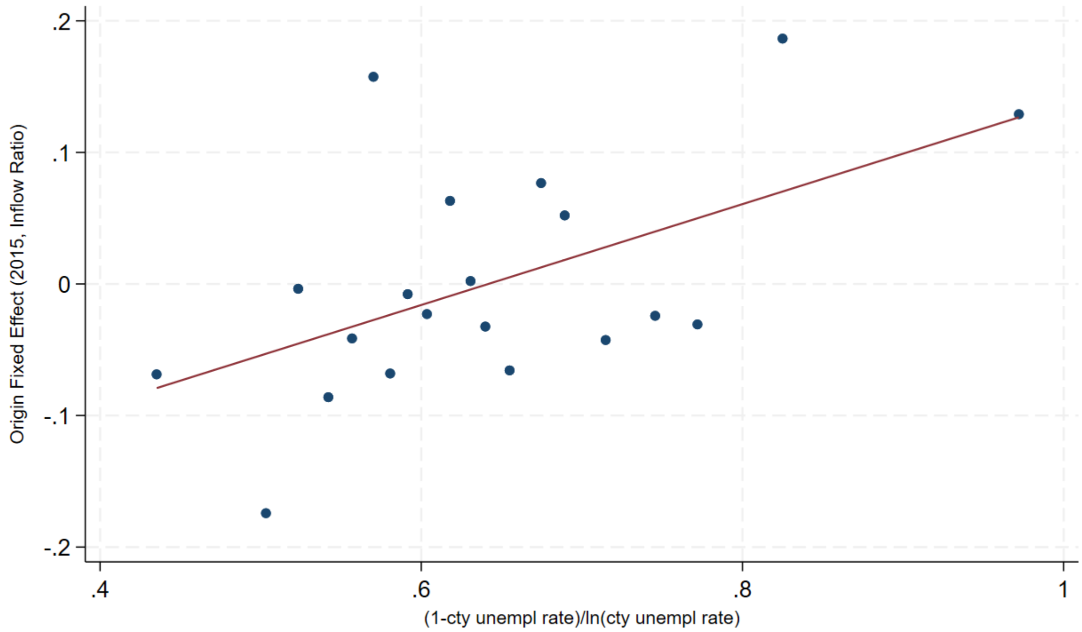
[52]This is defined slightly differently as the total number unemployed persons as share of the total civilian labor force above the age of 16, thus excluding in the denominator individuals who left a county as a result of migration.

**Table 7: Top Correlates of Status Quo Bias (Outflow Gravity Estimates)**

| | | | | | |
|---|---|---|---|---|---|
| **Commute** | | **Social Capital** | | **Industry of Employment** | |
| log avg. commute time | 0.060 | Republican Vote Share | 0.006 | % Construction Employment | 0.075 |
| % carpool | -0.025 | | | % Public Education, Health and Social Services Employment | 0.015 |
| % drive alone | 0.089 | **Religion (Adherent per 1,000)** | | % Finance, Insurance and Real Estate | 0.012 |
| | | Mainline Protestant | 0.018 | % Information Employment | -0.018 |
| **Housing** | | United Methodist Church | 0.036 | % Public Administration Employment | -0.030 |
| % built between 1940 and 1949 | 0.009 | Christian Churches / Churches of Christ | 0.010 | % Public Transportation Employment | 0.050 |
| % built between 1950 and 1959 | 0.016 | Amer. Baptist Churches | -0.005 | % Recreational and Entertainment Employment | -0.027 |
| % built between 1960 and 1969 | 0.022 | Evangelical Lutheran Church | -0.005 | % Transportation Employment | -0.010 |
| % built between 1980 and 1989 | -0.043 | Lutheran Church – Missouri Synod | -0.022 | % Wholesale Employment | 0.016 |
| % built between 1990 and 1999 | -0.032 | Latter-day Saints | -0.042 | | |
| % built between 2000 and 2009 | -0.086 | Southern Baptist Convention | -0.023 | **Demographics** | |
| % built between after 2010 | -0.099 | | | % Male | -0.094 |
| | | | | % aged older than 54 | 0.063 |
| **Climate** | | **Occupation** | | % younger than 20 | -0.069 |
| Heat Days | 0.013 | % Construction Occupation | -0.076 | % Black | -0.034 |
| Max Temp January | -0.088 | % Sales and Office Occupation | -0.014 | % Hispanic | 0.061 |
| Max Temp July | 0.049 | % Transportation and Utility Occupation | 0.042 | % Foreign-Born | 0.003 |
| | | | | % At Least Bachelors | -0.107 |
| | | | | % With Children | 0.147 |
| | | | | % Single Mothers | -0.011 |
| | | | | % Living Alone | 0.045 |
| | | | | % Divorced | -0.079 |

Note: This table lists the top contributors to county-level differences in estimated status quo bias and the corresponding coefficients. The analysis is based on a Least Absolute Shrinkage and Selection Operator (LASSO) estimator, and a cross-validation method that selects the shrinkage parameter according to minimum Bayesian information criterion. The full list of variables included in this exercise can be found in Appendix Table A4.

**Figure 4: Origin Fixed Effects from Inflow Regression (2015-2019) and the Unemployment Rate**




Notes. 1. This figure displays a binscatter plot of county-level origin fixed effects from the inflow ratio regression in Table A2 (2015-2019) and the corresponding employment ratio of the county $(1 - U_i)/\ln(U_i)$ where $U_i$ is the unemployment rate of county $i$ from the ACS.

These observations suggest that apart from serving as a primitive to aid status quo bias estimation, origin fixed effects can serve as a useful proxy to reflect location-specific expect utility and employment prospects. These have the potential to be particularly useful when standard metrics (e.g. wages, jobs, amenities) alone cannot fully capture the wide range of considerations workers take into account when selecting to stay put, or move away from their original location.

## 8 Conclusion

In this paper, we develop a model of migration in the presence of status quo bias in locational preference and job search frictions. The model delivers predictions about bilateral migration flows in a simple and tractable equation. As a theory of migration, we furnish a revised structural migration gravity equation with corresponding multilateral resistance terms that can be used to guide empirical analyses. We also illustrate how to use gravity estimates from outflow ratio, inflow ratio or geometric mean ratio regressions to back out status quo bias estimates. The new setting makes sense of why low mobility rates persist despite broad-based improvements in communication technologies. We also see that the iconic population-pair terms in migration gravity requires adjustment to account for unemployment in source and destination locations.

Using data on county-level population mobility in the U.S. and bilateral county-pair differences in historical ethnic, industry-of-employment, and occupational linkages as proxies for search frictions, we find that status quo bias estimates are dispersed and that this dispersion appears to have increased over time. A one-standard-deviation increase in log status quo bias has the same effect on the migration outflow ratio as a 39% reduction in the expected utility ratio, or an increase of 1,136 miles in distance between destination and origin counties. The difference in the migration ratio between otherwise identical in-state and out-of-state counties is equivalent to an interquartile-range increase in log status quo bias. These behavioral equivalents suggest that status quo bias generates migration frictions comparable to large geographic and institutional barriers.

Status quo bias estimates are strongly correlated over time and are associated with a rich set of non-wage individual and community-level markers of locational preference, shaped by lived experiences such as housing, climate, religion, and political orientation. In particular, status quo bias is well explained by factors reflecting family- and community-level identity, environmental adaptation, congestion, and housing considerations. These factors capture the consequences of dynamic locational preferences, including engagement with the local community, sunk investments in social networks, and commitments to housing and transportation.

The prevalence of status quo bias in county-to-county migration provides one explanation for low migration rates, despite strong economic incentives to relocate. Standard economic analyses of spatial labor allocation typically assume that moving costs are independent of migration history. This paper has three main implications for future research. First, motivated by a theory of migration under search frictions and location-history-dependent preferences, we show that the standard empirical gravity model of migration can be used to recover county-level status quo bias. This framework can be applied to other populations and historical periods to study the correlates of status quo bias. Second, because status quo bias creates a wedge between how newcomers and locals evaluate a location, the concept of labor misallocation can be extended to account for individual-specific migration costs. Incorporating status quo–based preferences into utility assessments helps reconcile persistent spatial disparities in economic opportunities with rational choice. Third, because locational preferences depend on migration history, even short-term policy interventions may have persistent effects on migration patterns. Future research could examine whether detailed local amenities amplify or mitigate status quo–driven locational preferences.

**Table 8: County Rankings: Top 20 Origin Fixed Effects Counties From Outflow Ratio Regression**

| 2015 Ranking | State | County | 2014 Ranking | State | County | 2005 Ranking | State | County |
|---|---|---|---|---|---|---|---|---|
| 1 | California | Los Angeles County | 1 | California | Los Angeles County | 1 | California | Los Angeles County |
| 2 | Illinois | Cook County | 2 | Illinois | Cook County | 2 | Illinois | Cook County |
| 3 | New York | Queens County | 3 | Texas | Harris County | 3 | Texas | Harris County |
| 4 | Texas | Harris County | 4 | Michigan | Wayne County | 4 | Michigan | Wayne County |
| 5 | Michigan | Wayne County | 5 | New York | Queens County | 5 | New York | Queens County |
| 6 | New York | Kings County | 6 | Florida | Miami-Dade County | 6 | Florida | Miami-Dade County |
| 7 | California | Orange County | 7 | California | Orange County | 7 | California | Riverside County |
| 8 | Pennsylvania | Philadelphia County | 8 | California | Riverside County | 8 | New York | Nassau County |
| 9 | Florida | Miami-Dade County | 9 | New York | Nassau County | 9 | Texas | Tarrant County |
| 10 | California | Riverside County | 10 | California | San Bernardino County | 10 | California | San Bernardino County |
| 11 | Texas | Dallas County | 11 | Texas | Dallas County | 11 | Texas | Dallas County |
| 12 | New York | Suffolk County | 12 | New York | Kings County | 12 | New York | Bronx County |
| 13 | California | San Bernardino County | 13 | Texas | Tarrant County | 13 | California | Orange County |
| 14 | New York | Nassau County | 14 | New York | Bronx County | 14 | Arizona | Maricopa County |
| 15 | Arizona | Maricopa County | 15 | New York | Suffolk County | 15 | New York | Suffolk County |
| 16 | Pennsylvania | Allegheny County | 16 | Pennsylvania | Philadelphia County | 16 | Pennsylvania | Philadelphia County |
| 17 | Texas | Tarrant County | 17 | Arizona | Maricopa County | 17 | New York | Kings County |
| 18 | Ohio | Cuyahoga County | 18 | Ohio | Cuyahoga County | 18 | Ohio | Cuyahoga County |
| 19 | New York | Bronx County | 19 | Florida | Broward County | 19 | Michigan | Oakland County |
| 20 | Michigan | Macomb County | 20 | New York | Westchester County | 20 | Michigan | Macomb County |

Notes. 1. This table lists the top 20 counties ranked based on estimated origin fixed effects calculated based on the outflow gravity regressions shown in Table 2.

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## Appendix A

In this appendix, we solve the model using a more general distribution function of utility draws $F_n(\omega, \cdot)$ satisfying two properties – (i) the power law to be defined below, and (ii) a common lower bound utility level. Specifically, let the probability distribution of each match-specific utility draw in location $n$, $\omega$, be given by $G_{nn}(\omega) = G_n(\omega, 1)$ for workers currently located in $n$ and searching in $n$, and $G_{mn}(\omega) = G_n(\omega, 1 + b_n)$, for workers currently in $m$, and searching in $n$. We continue to assume that:

$$G_n(\omega, 1 + b_n) \geq G_n(\omega, 1) \tag{32}$$

whenever $b_n \geq 0$. We let the distribution of utility draws ($\omega \geq \underline{\omega} \geq 0$) in destination $n$ be $G_n(\cdot, 1)$, where

$$G_n(\omega, 1) \quad = \quad 1 - w_n \phi(\omega)^{-1/\epsilon}, \;\; \text{if } m = n \tag{33}$$

where $\phi(\omega) \in [0, 1]$ is non-negative, increasing and continuously differentiable function of $\omega$ for $\omega \geq \underline{\omega} \geq 0$. $w_n \in (0, 1]$ is a shift parameter and $0 < \epsilon < 1$ is a shape parameter. Otherwise, if $m \neq n$,

$$G_n(\omega, 1 + b_n) \quad = \quad 1 - \frac{w_n}{1 + b_n} \phi(\omega)^{-1/\epsilon}, \;\; \text{if } \; m \neq n. \tag{34}$$

where $b_n \geq 0$ are is shift parameters accounting for status quo bias. The scaled generalized Pareto distribution function $F_n(\omega, 1)$ in the text is a special case where $\phi(\omega) = (1 + \epsilon\omega)$. The standard Pareto distribution function ($P_n = 1 - (\omega/e_n)^{-1/\epsilon}$) is also a special case, with $\phi(\omega) = \omega$, and $w_n = e_n^{1/\epsilon}$.

At each destination $n$, the probability distribution of the maximal utility sampled by a worker from $m$ seeking a job in destination $n$ is:

$$p_{mn}(\omega) \equiv \sum_{z_n=0}^{\infty} \frac{exp\left(-\lambda_{mn}\right)\left(\lambda_{mn}\right)^{z_n} G_{mn}(\omega)^{z_n}}{z_n!} = exp\left[-\lambda_{mn}(1 - G_{mn}(\omega))\right]. \tag{35}$$

$p_{mn}(\omega)$ is the probability that the highest utility job a worker finds is not better than $\omega$. Following the steps described in the text, the distribution of the highest offer for a worker from $m$ in destination $n$ is:

$$\begin{aligned} p_{mn}(\omega) &= exp\left[-\lambda_{mn}(1 - G_{mn}(\omega))\right] \\ &= \exp\left[-\lambda_{mn} w_n (1 + b_n)^{-\mathbb{I}_{mn}} \phi(\omega)^{-1/\epsilon}\right] \end{aligned} \tag{36}$$

The probability that a worker from $m$ finds that the best utility draw in $n$, $\omega_{mn}$, to be more appealing that any other one of the $M - 1$ locations's best offers, $\omega_{mk}$, $k \neq n$ is denoted as $\mu_{mn}$. In particular,

$$\mu_{mn} = \int_0^{\infty} Pr\left[\omega \geq \left\{\max_{k \neq n} \omega_{mk}\right\}\right] dp_{mn}(\omega).$$

By the law of large numbers, $\mu_{mn}$, the fraction of the workers in $m$ who prefers location $n$ to any of the other $M-1$ locations is:

$$\begin{aligned}\mu_{mn} &= \int_0^\infty \prod_{k\neq n} p_{mk}(\omega)dp_{mn}(\omega) \\ &= \left(\frac{\alpha_{mn}W_n}{\sum_{i=1}^M \alpha_{mi}W_i}\right)\left(1-exp\left[-\sum_{i=1}^M \alpha_{mi}W_i\phi(\underline{\omega})\right]\right). \end{aligned} \tag{37}$$

Thus, a similar gravity equation applies, and the only differences is that the expression $\left(1-exp\left[-\sum_{i=1}^M \alpha_{mi}W_i\phi(\underline{\omega})\right]\right)$ in equation (37) replaces $\left(1-exp\left[-\sum_{i=1}^M \alpha_{mi}W_i\right]\right)$ in equation (9).

**Proof of the Structural Gravity Equation in equation (11)**:
In this appendix, we demonstrate the structural gravity equation as displayed in equation (11). To start, let $M_{mn}=\mu_{mn}N_m$ denote total migration, and $L_n=\sum_m M_{mn}$ as total employment in $n$. From (9),

$$L_n = W_n\sum_m\left(\frac{\alpha_{mn}N_m(1-u_m)}{O_m}\right)$$

or equivalently

$$W_n = \frac{L_n}{I_n\sum_i N_i(1-u_i)}$$

where

$$I_n = \sum_m\left(\frac{\alpha_{mn}}{O_m}\frac{N_m(1-u_m)}{\sum_i N_i(1-u_i)}\right).$$

Substituting into (9), we obtain

$$M_{mn} = \frac{\alpha_{mn}}{O_m I_n}\frac{L_n\times[N_m(1-u_m)]}{\sum_i N_i(1-u_i)}$$

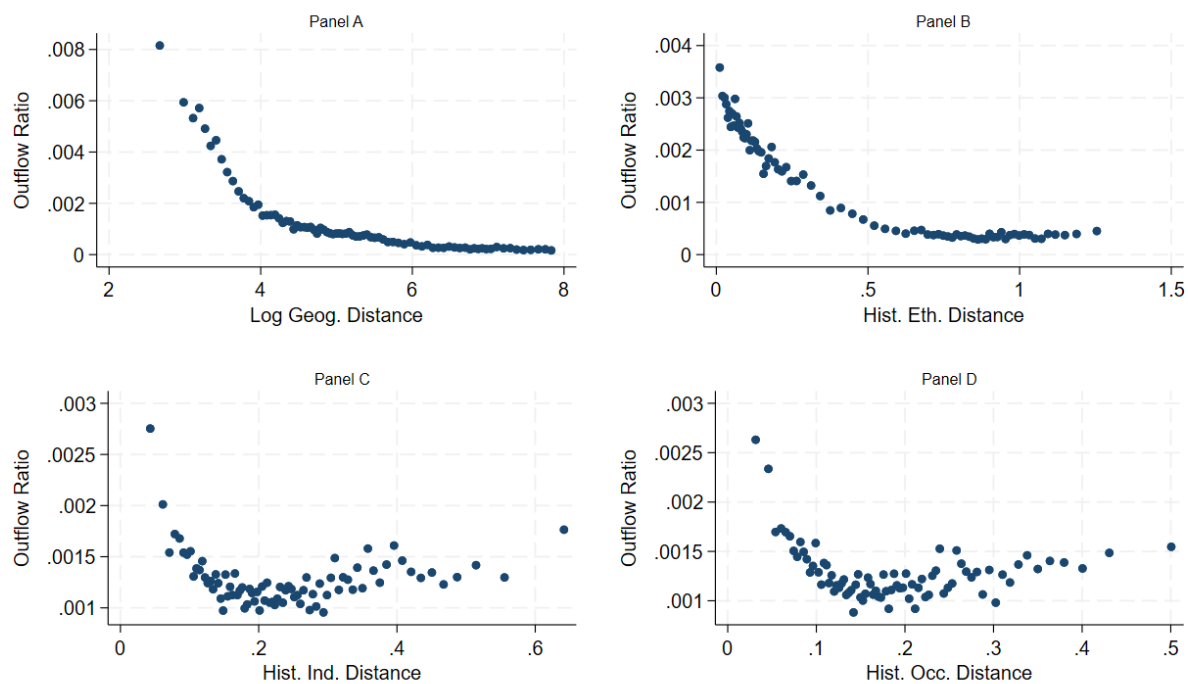
as displayed in (11) and

$$O_m = \sum_n \alpha_{mn}W_n = \sum_n \frac{\alpha_{mn}}{I_n}\frac{L_n}{\sum_i N_i(1-u_i)}$$

as displayed in (13). As discussed, total migration between two locations depends on (i) bilateral status quo bias adjusted search intensity $\alpha_{mn}$ normalized by both outward and inward multilateral resistance $O_m$ and $I_n$, (ii) a population product, involving the total number of employed workers native to $m$, $N_m(1-u_m)$, and the total number of employed workers (inclusive of migrants) in $n$, $L_n=\sum_m M_{mn}$. The employment product is normalized by the overall employment level $\sum_i N_i(1-u_i)$.

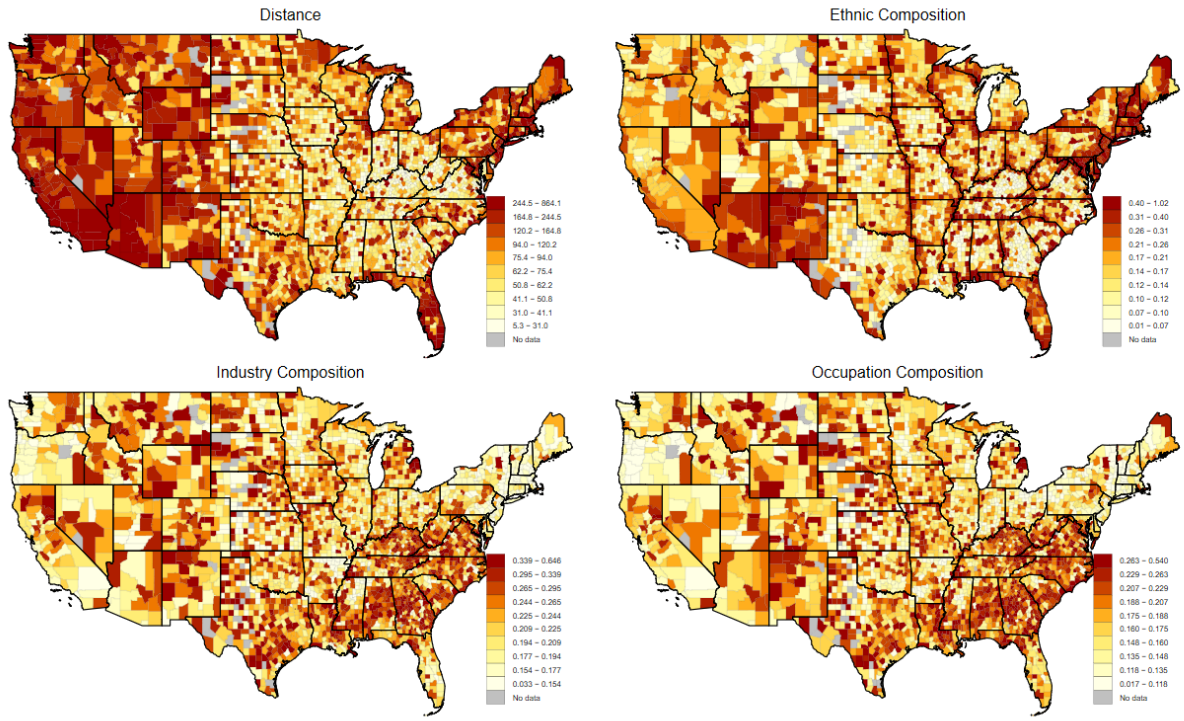
## Additional Figures and Tables

**Figure A1: Binscatter Plots of Population Outflow Ratios and Search Intensity Controls**



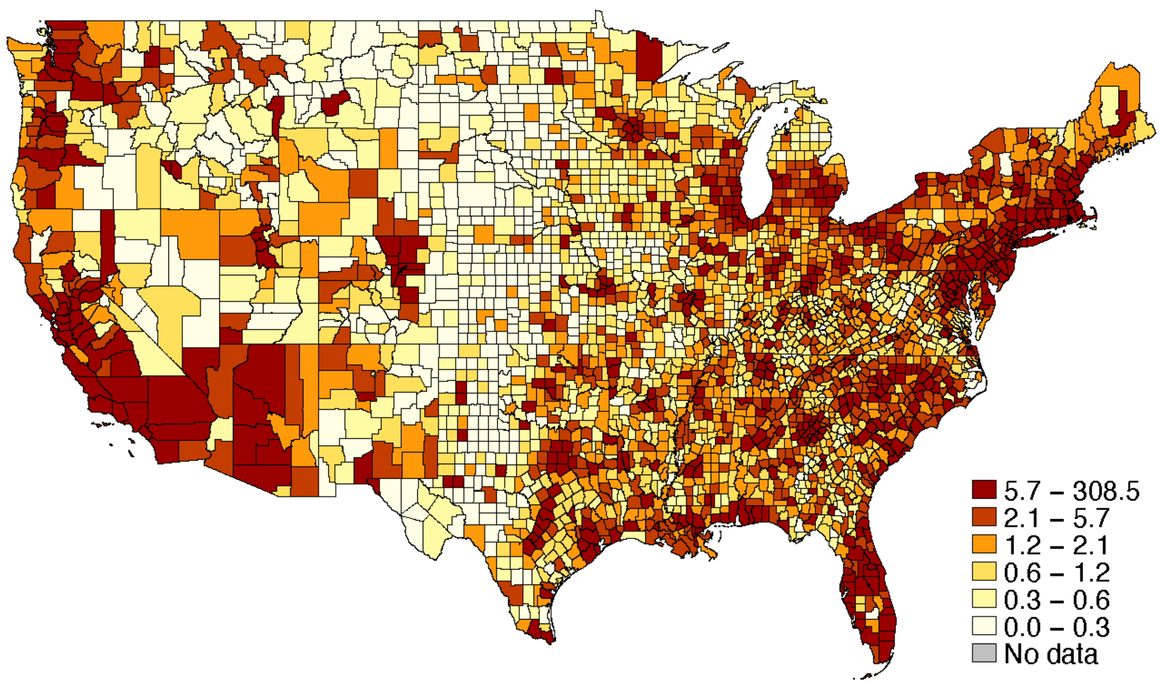

Notes. 1. This figure presents a binscatter plots of the relationship between U.S. county level population outflow ratio (bilateral population outflow / total non-movers at source, 2015-2019 average, ACS) and search intensity controls. 2. Historic ethnic distance is constructed according to equation (24) using historical (1940) county ethnic origin compositions from the public Census microdata. The ethnic origin distance measure is based on birthplace. Persons born in the 50 U.S. states are assigned their states of birth. To eliminate small cells, non-U.S. birthplaces are categorized into larger regions: U.S. territories, Canada, Mexico, other North America, South America, Central America, Western Europe, Central/Eastern Europe, Southern Europe, Northern Europe, Russian empire, East Asia, Southeast Asia, Southwest Asia, Middle East, and Oceania. Persons born at sea or with an unidentifiable birthplace are dropped from the analysis. 3. Historic industry-of-employment and historical occupation composition distance is similarly constructed according to equation (24) using historical (1940) industry and occupation composition shares. 4. Geographic distance is the distance between county pairs.

**Figure A2: Maps of Average Distance travelled and Search Friction Encountered by County-of-Origin**




Notes. 1. Panel A plots the average log geographic distance in miles traveled by emigrants at the county level based on chosen destination shares in 2015-2019. 2. Panel B plots the average historical ethnic composition distance experienced by emigrants at the county level based on chosen destination shares in 2015-2019. 3. Panel C plots the average historical industry of employment composition distance experienced by emigrants at the county level based on chosen destination shares in 2015-2019. 4. Panel D plots the average historical occupation composition distance experienced by emigrants at the county level based on chosen destination shares. 5. Historic ethnic distance is constructed according to equation (24) using historical (1940) county ethnic origin compositions from the public Census microdata. 6. The ethnic origin distance measure is based on birthplace. Persons born in the 50 U.S. states are assigned their states of birth. To eliminate small cells, non-U.S. birthplaces are categorized into larger regions: U.S. territories, Canada, Mexico, other North America, South America, Central America, Western Europe, Central/Eastern Europe, Southern Europe, Northern Europe, Russian empire, East Asia, Southeast Asia, Southwest Asia, Middle East, and Oceania. Persons born at sea or with an unidentifiable birthplace are dropped from the analysis. 7. Historic industry-of-employment and historical occupation composition distance is similarly constructed according to equation (24) using historical (1940) industry and occupation composition shares. 8. Geographic distance is the distance between county pairs.

**Figure A3: Geographic Distribution of Social Connectedness**




Notes. 1. This figure displays state-level average social connectedness using the Facebook Social Connectedness Index in equation (31).

**Table A1: Determinants of Population Outflow Ratios, Fixed Effects and Status Quo Bias Estimates for All Counties**

| | (1) Outflow 2005-09 | (2) Outflow 2014-18 | (3) Outflow 2015-19 |
|---|---|---|---|
| Log Geog. Distance (1,000 miles) | -0.449*** | -0.487*** | -0.486*** |
| | (0.006) | (0.006) | (0.006) |
| Same State Dummy | 0.461*** | 0.410*** | 0.402*** |
| | (0.037) | (0.041) | (0.041) |
| Log Hist. Eth. Distance | 0.230*** | 0.276*** | 0.261*** |
| | (0.063) | (0.069) | (0.070) |
| Log Hist. Ind. Distance | -0.739*** | -0.765*** | -0.732*** |
| | (0.102) | (0.108) | (0.109) |
| Log Hist. Occ. Distance | 0.140 | -0.098 | -0.100 |
| | (0.101) | (0.108) | (0.111) |
| Observations | 233770 | 262708 | 258933 |
| R2 | 0.698 | 0.649 | 0.649 |
| Variance Orig FE | 1.320 | 1.369 | 1.383 |
| Variance Dest FE | 0.359 | 0.416 | 0.429 |
| Max. Ln SQBIAS | 2.308 | 2.375 | 2.288 |
| Min. Ln SQBIAS | -4.460 | -4.083 | -3.906 |
| St Dev Ln SQBIAS | 0.742 | 0.697 | 0.692 |
| IQR Ln SQBIAS | 0.983 | 0.914 | 0.887 |

Notes. 1. This table displays the relationship between U.S. county level outflow ratio (bilateral population outflow / total non-movers at source, 2005-2009, 2014-2018, 2015-2019 average, ACS) and search intensity controls for all 3104 counties. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic origin composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23). Max. and Min. refer respectively to maximal and minimal estimates in the corresponding time period, and IQR is the interquartile range. 5. County-origin and county-destination fixed effects are included. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A2: Determinants of Population Inflow Ratios, Fixed Effects and Status Quo Bias Estimates**

| | (1) Inflow 2005-09 | (2) Inflow 2014-18 | (3) Inflow 2015-19 |
|---|---|---|---|
| Log Geog. Distance (1,000 miles) | -0.486*** | -0.493*** | -0.492*** |
| | (0.011) | (0.012) | (0.012) |
| Same State Dummy | 0.707*** | 0.811*** | 0.815*** |
| | (0.079) | (0.089) | (0.091) |
| Log Hist. Eth. Distance | -0.725*** | -0.721*** | -0.727*** |
| | (0.153) | (0.172) | (0.173) |
| Log Hist. Ind. Distance | -0.579*** | -0.648*** | -0.606*** |
| | (0.155) | (0.174) | (0.163) |
| Log Hist. Occ. Distance | 0.254 | 0.094 | 0.124 |
| | (0.201) | (0.222) | (0.218) |
| Observations | 81111 | 86021 | 85196 |
| R2 | 0.546 | 0.499 | 0.497 |
| Variance Orig FE | 0.155 | 0.185 | 0.184 |
| Variance Dest FE | 0.192 | 0.321 | 0.316 |
| Max. log SQBIAS | 1.322 | 1.640 | 1.579 |
| Min. log SQBIAS | -1.611 | -1.772 | -1.791 |
| St Dev Ln SQBIAS | 0.494 | 0.518 | 0.509 |
| IQR log SQBIAS | 0.707 | 0.765 | 0.772 |

Notes. 1. This table displays the relationship between U.S. county level population inflow ratio (bilateral population outflow / total non-movers at destination, 2005-2009, 2014-2018, 2015-2019 average, ACS) and search intensity controls. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic origin composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23). Max. and Min. refer respectively to maximal and minimal estimates in the corresponding time period, and IQR is the interquartile range. 5. County-origin and county-destination fixed effects are included. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A3: Determinants of Population Geometric Mean Flow Ratios, Fixed Effects and Status Quo Bias Estimates**

| | (1) Geometric Mean 2005-09 | (2) Geometric Mean 2014-18 | (3) Geometric Mean 2015-19 |
|---|---|---|---|
| Log Geog. Distance (1,000 miles) | -0.486*** | -0.493*** | -0.492*** |
| | (0.011) | (0.012) | (0.012) |
| Same State Dummy | 0.707*** | 0.811*** | 0.815*** |
| | (0.079) | (0.089) | (0.091) |
| Log Hist. Eth. Distance | -0.724*** | -0.721*** | -0.727*** |
| | (0.153) | (0.172) | (0.173) |
| Log Hist. Ind. Distance | -0.580*** | -0.647*** | -0.605*** |
| | (0.155) | (0.174) | (0.163) |
| Log Hist. Occ. Distance | 0.254 | 0.094 | 0.124 |
| | (0.201) | (0.222) | (0.218) |
| Observations | 81111 | 86021 | 85196 |
| R2 | 0.407 | 0.374 | 0.372 |
| Variance Orig FE | 0.045 | 0.048 | 0.048 |
| Variance Dest FE | 0.098 | 0.120 | 0.118 |
| Max. log SQBIAS | 1.322 | 1.640 | 1.579 |
| Min. log SQBIAS | -1.611 | -1.772 | -1.791 |
| St Dev Ln SQBIAS | 0.494 | 0.518 | 0.509 |
| IQR log SQBIAS | 0.707 | 0.765 | 0.772 |

Notes. 1. This table displays the relationship between the geometric mean of U.S. county level population outflow and Inflow ratios (bilateral population outflow / (total non-movers at destination x total non-movers at source)$^{0.5}$, 2005-2009, 2014-2018, 2015-2019 average, ACS) and search intensity controls. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic origin composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23). Max. and Min. refer respectively to maximal and minimal estimates in the corresponding time period, and IQR is the interquartile range. 5. County-origin and county-destination fixed effects are included. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A4: List of Variables in Lasso Regressions.**

| Variable Group | Variable List |
|---|---|
| Commute | log avg. commute time, % commuters, % drive alone, % carpool, % take public transport |
| Housing | % housing built 2010 or later, % built between 2000 and 2009, % built between 1990 and 1999, % built between 1980 and 1989, % built between 1970 and 1979, % built between 1960 and 1969, % built between 1950 and 1950, % built between 1940 and 1949, % built before 1940 |
| Environment | heat days, max. January temperature, max. July temperature |
| Social Capital | crime per capita, and republican vote share |
| Religious | % Evangelical, % Catholic, % Mainline Protestant, % American Baptist Churches, % Christian Churhes & Churches of Christ, % Evangelical Lutheran Church, % Lutheran Church – Missouri Synod, % Latter-day Saints, % Southern Baptist Convention |
| Industry of employment | % agriculture, % construction, % manufacturing, % whole sale, % retail, % transportation, % information, % finance, insurance, and real estate, % public education, health, and social services, % recreational and entertainment, % other industries, and % public admin |
| Marriage | % living alone, % with children, % divorced, % grand parents caring for children |
| Occupation | % management and professional, % construction, % farm and fish, % sales and office, % service, % transportation and utility |
| Demographics | % males, % black, % Hispanic, % foreign-born, % with at least Bachelor's, log population density, % younger than 20, % aged between 20 and 54, % aged older than 54 |

**Table A5: Full List of Predictors of Status Quo Bias (Outflow Gravity Estimates)**

| | | | | | |
|---|---|---|---|---|---|
| **Commute** | | **Social Capital** | | **Industry of Employment** | |
| log avg. commute time | 0.063 | Republican Vote Share | 0.013 | % Construction Employment | 0.077 |
| % carpool | -0.023 | | | % Public Education, Health and Social Services Employment | 0.019 |
| % drive alone | 0.077 | **Religion (Adherent per 1,000)** | | % Finance, Insurance and Real Estate | 0.010 |
| | | Catholic | 0.003 | % Information Employment | -0.015 |
| **Housing** | | Mainline Protestant | 0.025 | % Public Administration Employment | -0.027 |
| % built between 1940 and 1949 | 0.001 | United Methodist Church | 0.036 | % Public Transportation Employment | 0.034 |
| % built between 1950 and 1959 | 0.014 | Amer. Baptist Churches | -0.008 | % Recreational and Entertainment Employment | -0.030 |
| % built between 1960 and 1969 | 0.018 | Christian Churches Churches of Christ | 0.008 | % Transportation Employment | -0.009 |
| % built between 1970 and 1979 | -0.035 | Evangelical Lutheran Church | -0.010 | % Wholesale Employment | 0.017 |
| % built between 1980 and 1989 | -0.048 | Lutheran Church – Missouri Synod | -0.019 | | |
| % built between 1990 and 1999 | -0.032 | Latter-day Saints | -0.041 | **Demographics** | |
| % built between 2000 and 2009 | -0.090 | Southern Baptist Convention | -0.017 | % Male | -0.099 |
| % built between after 2010 | -0.100 | | | % aged older than 54 | 0.057 |
| | | **Occupation** | | % younger than 20 | -0.075 |
| **Environment** | | % Construction Occupation | -0.077 | % Black | -0.031 |
| Heat Days | 0.017 | % Sales and Office Occupation | -0.012 | % Hispanic | 0.053 |
| Max Temp January | -0.087 | % Transportation and Utility Occupation | 0.051 | % Foreign-Born | 0.002 |
| Max Temp July | 0.046 | | | % At Least Bachelors | -0.104 |
| | | | | % With Children | 0.147 |
| | | | | % Single Mothers | -0.008 |
| | | | | % Living Alone | 0.045 |
| | | | | % Divorced | -0.087 |

Note: This table lists the top contributors to county-level differences in estimated status quo bias and the corresponding coefficients. The analysis is based on a Least Absolute Shrinkage and Selection Operator (LASSO) estimator, and a cross-validation method that selects the shrinkage parameter according to minimum Bayesian information criterion. The full list of variables included in this exercise can be found in Appendix Table A4.

# Online Appendix A

In this appendix, we reproduce the key results of this study when we alter the definition of large counties to include only those with labor force greater than 100,000. Tables A6 - A8 are the counterparts of Tables 2, A2 - A3 showing migration gravity and status quo bias estimates with the revised definition of large counties as counties with labor force higher than 100,000 in 2015. We see that altering the definition of large counties does not change the signs of the estimated coefficients. The coefficients associated with historical search frictions are larger in absolute value as seen in Figure 1a. The resulting status quo bias estimates are more dispersed among larger counties, showing wider (maximum-to-minimum and interquartile) ranges. Like Tables 2, A2 - A3, the dispersion in status quo bias estimates also seem to be rising over time. Thus, changing the definition of large counties produce similar qualitative findings as shown in the main text, while reducing the number of observations almost by half.

In Table A10, we see that this sub-sample of the largest counties features a wider range in in the relative Shapley value contribution of the historical status quo bias estimates to the overall R2 of future (2015-2019, 2014-2018) outflow and inflow ratio regressions. The geometric mean migration ratio, which utilizes the geometric mean of the origin and destination nonmovers as the migration ratio numeraire, yield Shapley value R2 contribution of the historical status quo bias estimates at around 8%, which is in line with the findings in the main text.

**Table A6: Determinants of Population Outflow Ratios, Fixed Effects and Status Quo Bias Estimates (Large Counties)**

| | (1) Outflow 2005-09 | (2) Outflow 2014-18 | (3) Outflow 2015-19 |
|---|---|---|---|
| Ln Geog. Distance | -0.521*** | -0.521*** | -0.519*** |
| | (0.015) | (0.015) | (0.015) |
| Same State Dummy | 0.557*** | 0.662*** | 0.660*** |
| | (0.093) | (0.092) | (0.095) |
| Log Hist. Eth. Distance | -1.697*** | -1.719*** | -1.745*** |
| | (0.192) | (0.205) | (0.204) |
| Log Hist. Ind. Distance | -0.530** | -0.628** | -0.698*** |
| | (0.213) | (0.245) | (0.229) |
| Log Hist. Occ. Distance | 0.407 | 0.117 | 0.333 |
| | (0.304) | (0.330) | (0.325) |
| Observations | 44066 | 46382 | 46148 |
| R2 | 0.532 | 0.502 | 0.497 |
| Variance Orig FE | 0.173 | 0.151 | 0.150 |
| Variance Dest FE | 0.208 | 0.267 | 0.259 |
| Max. Ln SQBIAS | 1.448 | 1.780 | 1.699 |
| Min. Ln SQBIAS | -1.685 | -1.331 | -1.314 |
| St Dev Ln SQBIAS | 0.531 | 0.565 | 0.551 |
| IQR Ln SQBIAS | 0.784 | 0.820 | 0.806 |

Notes. 1. This table displays the relationship between U.S. county level population outflow ratio (bilateral population outflow / total non-movers at source, 2005-2009, 2014-2018, 2015-2019 average, ACS, for counties with labor force greater than 100,000 in 2015-2019.) and search intensity controls. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23). Max. and Min. refer respectively to maximal and minimal estimates in the corresponding time period, and IQR is the interquartile range. 5. County-origin and county-destination fixed effects are included. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A7: Determinants of Population Inflow Ratios, Fixed Effects and Status Quo Bias Estimates (Large Counties)**

| | (1) Inflow 2005-09 | (2) Inflow 2014-18 | (3) Inflow 2015-19 |
|---|---|---|---|
| Log Geog. Distance (1000 miles) | -0.521*** | -0.521*** | -0.519*** |
| | (0.015) | (0.015) | (0.015) |
| Same State Dummy | 0.557*** | 0.662*** | 0.660*** |
| | (0.093) | (0.092) | (0.095) |
| Log Hist. Eth. Distance | -1.697*** | -1.719*** | -1.745*** |
| | (0.192) | (0.205) | (0.204) |
| Log Hist. Ind. Distance | -0.530** | -0.628** | -0.698*** |
| | (0.213) | (0.245) | (0.229) |
| Log Hist. Occ. Distance | 0.407 | 0.117 | 0.333 |
| | (0.304) | (0.330) | (0.325) |
| Observations | 44066 | 46382 | 46148 |
| R2 | 0.543 | 0.509 | 0.504 |
| Variance Orig FE | 0.182 | 0.203 | 0.202 |
| Variance Dest FE | 0.208 | 0.276 | 0.268 |
| Max. Ln SQBIAS | 1.448 | 1.780 | 1.699 |
| Min. Ln SQBIAS | -1.685 | -1.331 | -1.314 |
| St Dev Ln SQBIAS | 0.531 | 0.565 | 0.551 |
| IQR Ln SQBIAS | 0.784 | 0.820 | 0.806 |

Notes. 1. This table displays the relationship between U.S. county level population inflow ratio (bilateral population outflow / total non-movers at destination, 2005-2009, 2014-2018, 2015-2019 average, ACS, for counties with labor force greater than 100,000 in 2015-2019.) and search intensity controls. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic origin composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23). Max. and Min. refer respectively to maximal and minimal estimates in the corresponding time period, and IQR is the interquartile range. 5. County-origin and county-destination fixed effects are included. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A8: Determinants of Population Geometric Mean Flow Ratios, Fixed Effects and Status Quo Bias Estimates (Large Counties)**

| | (1)<br>Geometric<br>Mean 2005-09 | (2)<br>Geometric<br>Mean 2014-18 | (3)<br>Geometric<br>Mean 2015-19 |
|---|---|---|---|
| Log Geog. Distance (1,000 miles) | -0.521*** | -0.521*** | -0.519*** |
| | (0.015) | (0.015) | (0.015) |
| Same State Dummy | 0.557*** | 0.662*** | 0.660*** |
| | (0.093) | (0.092) | (0.095) |
| Log Hist. Eth. Distance | -1.697*** | -1.719*** | -1.745*** |
| | (0.192) | (0.205) | (0.204) |
| Log Hist. Ind. Distance | -0.530** | -0.628** | -0.698*** |
| | (0.213) | (0.245) | (0.229) |
| Log Hist. Occ. Distance | 0.407 | 0.117 | 0.333 |
| | (0.304) | (0.330) | (0.325) |
| Observations | 44066 | 46382 | 46148 |
| R2 | 0.438 | 0.413 | 0.408 |
| Variance Orig FE | 0.048 | 0.052 | 0.051 |
| Variance Dest FE | 0.116 | 0.147 | 0.139 |
| Max. Ln SQBIAS | 1.448 | 1.780 | 1.699 |
| Min. Ln SQBIAS | -1.685 | -1.331 | -1.314 |
| St Dev Ln SQBIAS | 0.531 | 0.565 | 0.551 |
| IQR Ln SQBIAS | 0.784 | 0.820 | 0.806 |

Notes. 1. This table displays the relationship between the geometric mean of U.S. county level population outflow and Inflow ratios (bilateral population outflow / (total non-movers at destination x total non-movers at source)$^{0.5}$, 2005-2009, 2014-2018, 2015-2019 average, ACS, for counties with labor force greater than 100,000 in 2015-2019.) and search intensity controls. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic origin composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23). Max. and Min. refer respectively to maximal and minimal estimates in the corresponding time period, and IQR is the interquartile range. 5. County-origin and county-destination fixed effects are included. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A9: Determinants of Population Flow Ratios with Historical Fixed Effects and Status Quo Bias Estimates (Large Counties)**

| | (1)<br>Outflow<br>2015-19 | (2)<br>Inflow<br>2015-19 | (3)<br>Geometric Mean<br>2015-19 | (4)<br>Outflow<br>2014-18 | (5)<br>Inflow<br>2014-18 | (6)<br>Geometric Mean<br>2014-18 |
|---|---|---|---|---|---|---|
| Log Geog. Distance (1000 miles) | -0.566*** | -0.561*** | -0.545*** | -0.561*** | -0.559*** | -0.542*** |
| | (0.013) | (0.013) | (0.012) | (0.014) | (0.014) | (0.013) |
| Same State Dummy | 0.534*** | 0.540*** | 0.487*** | 0.521*** | 0.530*** | 0.475*** |
| | (0.065) | (0.066) | (0.067) | (0.062) | (0.063) | (0.064) |
| Log Std. Hist. Eth. Distance | -1.876*** | -1.882*** | -2.005*** | -1.913*** | -1.910*** | -2.038*** |
| | (0.103) | (0.107) | (0.109) | (0.098) | (0.100) | (0.103) |
| Log Std. Hist. Ind. Distance | -0.404* | -0.385 | -0.462** | -0.426* | -0.398* | -0.475** |
| | (0.225) | (0.238) | (0.225) | (0.223) | (0.237) | (0.223) |
| Log Std. Occ. Distance | -0.116 | -0.124 | -0.169 | -0.213 | -0.218 | -0.266 |
| | (0.277) | (0.290) | (0.276) | (0.266) | (0.282) | (0.267) |
| Hist. Origin FE (2005, Outflow) | 0.823*** | | | 0.838*** | | |
| | (0.031) | | | (0.031) | | |
| Hist. Dest. FE, Adj. (2005, Outflow) | 1.099*** | | | 1.107*** | | |
| | (0.038) | | | (0.038) | | |
| Hist. Log Status Quo Bias (2005, Outflow) | -1.124*** | | | -1.133*** | | |
| | (0.032) | | | (0.031) | | |
| Hist. Origin FE (2005, Inflow) | | 1.077*** | | | 1.085*** | |
| | | (0.032) | | | (0.033) | |
| Hist. Dest. FE, Adj. (2005, Inflow) | | 0.870*** | | | 0.858*** | |
| | | (0.033) | | | (0.034) | |
| Hist. Log Status Quo Bias (2005, Inflow) | | -0.929*** | | | -0.942*** | |
| | | (0.030) | | | (0.028) | |
| Hist. Origin FE (2005, Geo.) | | | 0.900*** | | | 0.929*** |
| | | | (0.062) | | | (0.063) |
| Hist. Dest. FE, Adj. (2005, Geo.) | | | 0.752*** | | | 0.690*** |
| | | | (0.174) | | | (0.173) |
| Hist. Log Status Quo Bias (2005, Geo.) | | | -0.928*** | | | -0.917*** |
| | | | (0.056) | | | (0.056) |
| Observations | 36517 | 36517 | 36517 | 36737 | 36737 | 36737 |
| R2 | 0.510 | 0.519 | 0.424 | 0.515 | 0.523 | 0.428 |

Notes. 1. This table displays the determinants of U.S. county level population outflow ratio, inflow ratio and geometric mean ratio for counties with labor force greater than 100,000 in 2015-2019. 2. This table differs from Tables A6, A7 and A8 in that origin fixed effects are replaced by estimated origin fixed effects from 2005. 3. Adjusted historical destination fixed effect are the counterfactual destination fixed effects if there were no status quo bias, or the historical origin fixed effect of the corresponding county. 4. Historical status quo bias are the log status quo bias estimates from 2005. 5. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: **Shapley Decomposition with Historical (2005) Location Fixed Effects and Status Quo Bias Estimates**

| | Outflow 2015-19 (%) | Inflow 2015-19 (%) | Geometric Mean 2015-19 (%) | Outflow 2014-18 (%) | Inflow 2014-18 (%) | Geometric Mean 2014-18 (%) |
|---|---|---|---|---|---|---|
| Log Geog. Distance | 26.67 | 25.45 | 37.82 | 26.01 | 25.05 | 37.19 |
| Same State Dummy | 19.45 | 18.54 | 27.45 | 19.25 | 18.46 | 27.29 |
| Hist. Search Frictions Controls | 16.8 | 15.51 | 23.26 | 16.88 | 15.66 | 23.48 |
| Hist. Origin FE (2005) | 13.83 | 18.48 | 2.77 | 14.12 | 18.76 | 2.97 |
| Hist. Dest. FE. Adj. (2005) | 9.14 | 13.3 | 2.48 | 9.29 | 12.86 | 2.65 |
| Hist. Log Status Quo Bias (2005) | 14.11 | 8.72 | 6.22 | 14.45 | 9.2 | 6.4 |

Notes. 1. This table presents the Shapley Decomposition of the overall R2 of the six regressions in Table A9. 2. Six groups of control variables are used, including log geographic distance, the same state dummy, the three historical search frictions controls, historical origin fixed effects, historical destination fixed effects adjusted to reflect the counterfactual scenario where there is no status quo bias, and finally, the historical status quo bias estimate. 3. The historical fixed effects and status quo bias estimates are taken from the 2005 migration gravity regressions in Table A6, A7 and A8.

## Online Appendix B

In this appendix, we reproduce the key results of this study using the subsample of small counties with labor force less than 50,000. Tables A11 - A13 are the counterparts of Tables 2, A2 - A3 showing migration gravity and status quo bias estimates for the subsample of small county pairs with labor force less than 50,000. As discussed in the text, the subsample of small counties respond to historical search controls differently – the coefficients are small in absolute values and of the wrong sign for ethnic composition distance as seen in Figure 1a. The resulting status quo bias estimates are more dispersed , showing wider (maximum-to-minimum and interquartile) ranges as shown in Table A11, A12 and A13.

In Table A15, we see that in this sub-sample of the smallest counties, historical status quo bias estimates feature a wider range of relative Shapley value contribution to the overall R2 of future (2015-2019, 2014-2018) migration ratio regressions. The geometric mean migration ratio, which utilizes the geometric mean of the origin and destination nonmovers as the migration ratio numeraire, yield Shapley value R2 contribution of the historical status quo bias estimates at around 8%, which is in line with the findings in the main text.

**Table A11: Determinants of Population Outflow Ratios, Fixed Effects and Status Quo Bias Estimates (Small Counties)**

| | (1) Outflow 2005-09 | (2) Outflow 2014-18 | (3) Outflow 2015-19 |
|---|---|---|---|
| Log Geog. Distance | -0.437*** | -0.498*** | -0.492*** |
| | (0.007) | (0.008) | (0.008) |
| Same State Dummy | -0.065* | -0.049 | -0.052 |
| | (0.039) | (0.048) | (0.049) |
| Log Hist. Eth. Distance | 0.040 | 0.240*** | 0.206** |
| | (0.067) | (0.080) | (0.081) |
| Log Hist. Ind. Distance | -0.256** | -0.386*** | -0.318** |
| | (0.128) | (0.133) | (0.136) |
| Log Hist. Occ. Distance | 0.053 | 0.168 | 0.148 |
| | (0.145) | (0.146) | (0.149) |
| Observations | 53578 | 66396 | 65430 |
| R2 | 0.488 | 0.447 | 0.448 |
| Variance Orig FE | 0.795 | 0.837 | 0.851 |
| Variance Dest FE | 0.258 | 0.253 | 0.268 |
| Max. Ln SQBIAS | 2.797 | 2.239 | 2.032 |
| Min. Ln SQBIAS | -4.096 | -4.218 | -3.880 |
| St Dev Ln SQBIAS | 0.639 | 0.657 | 0.653 |
| IQR Ln SQBIAS | 0.805 | 0.833 | 0.819 |

Notes. 1. This table displays the relationship between U.S. county level population outflow ratio (bilateral population outflow / total non-movers at source, 2005-2009, 2014-2018, 2015-2019 average, ACS) and search intensity controls for county pairs with labor force at less than 50,000 in 2015-2019. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic origin composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23. Max. and Min. refer respectively to maximal and minimal estimates in the corresponding time period, and IQR is the interquartile range. 5. County-origin and county-destination fixed effects are included. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A12: Determinants of Population Inflow Ratios, Fixed Effects and Status Quo Bias Estimates (Small Counties)**

| | (1) Inflow 2005-09 | (2) Inflow 2014-18 | (3) Inflow 2015-19 |
|---|---|---|---|
| Log Geog. Distance | -0.437*** | -0.498*** | -0.492*** |
| | (0.007) | (0.008) | (0.008) |
| Same State Dummy | -0.065* | -0.049 | -0.052 |
| | (0.039) | (0.048) | (0.049) |
| Log Hist. Eth. Distance | 0.040 | 0.240*** | 0.206** |
| | (0.067) | (0.080) | (0.081) |
| Log Hist. Ind. Distance | -0.256** | -0.386*** | -0.318** |
| | (0.128) | (0.133) | (0.136) |
| Log Hist. Occ. Distance | 0.053 | 0.168 | 0.148 |
| | (0.145) | (0.146) | (0.149) |
| Observations | 53578 | 66396 | 65430 |
| R2 | 0.435 | 0.388 | 0.384 |
| Variance Orig FE | 0.109 | 0.128 | 0.125 |
| Variance Dest FE | 0.631 | 0.620 | 0.601 |
| Max. Ln SQBIAS | 2.797 | 2.239 | 2.032 |
| Min. Ln SQBIAS | -4.096 | -4.218 | -3.880 |
| St Dev Ln SQBIAS | 0.639 | 0.657 | 0.653 |
| IQR Ln SQBIAS | 0.805 | 0.833 | 0.819 |

Notes. 1. This table displays the relationship between U.S. county level population inflow ratio (bilateral population outflow / total non-movers at destination, 2005-2009, 2014-2018, 2015-2019 average, ACS) and search intensity controls for all county pairs except those with origin and destination labor force greater than 50,000 in 2015-2019. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic origin composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23). Max. and Min. refer respectively to maximal and minimal estimates in the corresponding time period, and IQR is the interquartile range. 5. County-origin and county-destination fixed effects are included. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A13: Determinants of Population Geometric Mean Flow Ratios, Fixed Effects and Status Quo Bias Estimates (Small Counties)**

| | (1) Geometric Mean 2005-09 | (2) Geometric Mean 2014-18 | (3) Geometric Mean 2015-19 |
|---|---|---|---|
| Log Geog. Distance (1,000 miles) | -0.437*** | -0.498*** | -0.492*** |
| | (0.007) | (0.008) | (0.008) |
| Same State Dummy | -0.065* | -0.049 | -0.052 |
| | (0.039) | (0.048) | (0.049) |
| Log Hist. Eth. Distance | 0.040 | 0.240*** | 0.206** |
| | (0.067) | (0.080) | (0.081) |
| Log Hist. Ind. Distance | -0.256** | -0.386*** | -0.318** |
| | (0.128) | (0.133) | (0.136) |
| Log Hist. Occ. Distance | 0.053 | 0.168 | 0.148 |
| | (0.145) | (0.146) | (0.149) |
| Observations | 53578 | 66396 | 65430 |
| R2 | 0.368 | 0.323 | 0.321 |
| Variance Orig FE | 0.210 | 0.233 | 0.235 |
| Variance Dest FE | 0.203 | 0.187 | 0.181 |
| Max. Ln SQBIAS | 2.797 | 2.239 | 2.032 |
| Min. Ln SQBIAS | -4.096 | -4.218 | -3.880 |
| St Dev Ln SQBIAS | 0.639 | 0.657 | 0.653 |
| IQR Ln SQBIAS | 0.805 | 0.833 | 0.819 |

Notes. 1. This table displays the relationship between the geometric mean of U.S. county level population outflow and Inflow ratios (bilateral population outflow / (total non-movers at destination x total non-movers at source)$^{0.5}$, 2005-2009, 2014-2018, 2015-2019 average, ACS) and search intensity controls for all county pairs except those with origin and destination labor force greater than 50,000 in 2015-2019. 2. Three search frictions controls are included: "Hist. Eth. Distance", "Hist. Ind. Distance" and "Hist. Occ. Distance" respectively refer to historical ethnic origin composition distance, historical industry-of-employment composition distance, and occupation composition distance defined in (24). "Geog. Distance", and "Same State Dummy" refers to geographic distance (1,000 miles), and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation (23). Max. and Min. refer respectively to maximal and minimal estimates in the corresponding time period, and IQR is the interquartile range. 5. County-origin and county-destination fixed effects are included. 6. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A14: Determinants of Population Flow Ratios with Historical Fixed Effects and Status Quo Bias Estimates (Small Counties)

| | (1)<br>Outflow<br>2015-19 | (2)<br>Inflow<br>2015-19 | (3)<br>Geometric Mean<br>2015-19 | (4)<br>Outflow<br>2014-18 | (5)<br>Inflow<br>2014-18 | (6)<br>Geometric Mean<br>2014-18 |
|---|---|---|---|---|---|---|
| Log Geog. Distance (1,000 miles) | -0.698*** | -0.700*** | -0.698*** | -0.718*** | -0.718*** | -0.718*** |
| | (0.016) | (0.016) | (0.016) | (0.017) | (0.016) | (0.016) |
| Same State Dummy | 0.138* | 0.142** | 0.137* | 0.148** | 0.155** | 0.148** |
| | (0.071) | (0.072) | (0.070) | (0.076) | (0.076) | (0.075) |
| Log Std. Hist. Eth. Distance | 0.038 | 0.033 | 0.027 | 0.057 | 0.057 | 0.045 |
| | (0.125) | (0.126) | (0.123) | (0.133) | (0.133) | (0.132) |
| Log Std. Hist. Ind. Distance | -0.217 | -0.322 | -0.220 | -0.053 | -0.155 | -0.053 |
| | (0.225) | (0.224) | (0.221) | (0.219) | (0.220) | (0.216) |
| Log Std. Occ. Distance | -0.067 | 0.062 | -0.001 | -0.238 | -0.095 | -0.167 |
| | (0.252) | (0.253) | (0.250) | (0.250) | (0.252) | (0.248) |
| Hist. Origin FE (2005, Outflow) | 0.851*** | | | 0.835*** | | |
| | (0.014) | | | (0.015) | | |
| Hist. Dest. FE, Adj. (2005, Outflow) | 0.836*** | | | 0.820*** | | |
| | (0.025) | | | (0.024) | | |
| Hist. Log Status Quo Bias (2005, Outflow) | -0.660*** | | | -0.671*** | | |
| | (0.029) | | | (0.029) | | |
| Hist. Origin FE (2005, Inflow) | | 0.698*** | | | 0.699*** | |
| | | (0.036) | | | (0.036) | |
| Hist. Dest. FE, Adj. (2005, Inflow) | | 0.628*** | | | 0.641*** | |
| | | (0.036) | | | (0.037) | |
| Hist. Log Status Quo Bias (2005, Inflow) | | -0.763*** | | | -0.781*** | |
| | | (0.017) | | | (0.017) | |
| Hist. Origin FE (2005, Geo.) | | | 0.597*** | | | 0.572*** |
| | | | (0.026) | | | (0.027) |
| Hist. Dest. FE, Adj. (2005, Geo.) | | | 0.313*** | | | 0.301*** |
| | | | (0.045) | | | (0.044) |
| Hist. Log Status Quo Bias (2005, Geo.) | | | -0.493*** | | | -0.510*** |
| | | | (0.028) | | | (0.027) |
| Observations | 21017 | 21017 | 21017 | 21141 | 21141 | 21141 |
| R2 | 0.361 | 0.303 | 0.259 | 0.366 | 0.315 | 0.270 |

Notes. 1. This table displays the determinants of U.S. county level population outflow ratio, inflow ratio and geometric mean ratio for counties with labor force less than 50,000 in 2015-2019. 2. This table differs from Tables A11, A12 and A13 in that origin fixed effects are replaced by estimated origin fixed effects from 2005. 3. Adjusted historical destination fixed effect are the counterfactual destination fixed effects if there were no status quo bias, or the historical origin fixed effect of the corresponding county. 4. Historical status quo bias are the log status quo bias estimates from 2005. 5. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A15: Shapley Decomposition with Historical Fixed Effects and Status Quo Bias Estimates**

| | Outflow 2015-19 (%) | Inflow 2015-19 (%) | Geometric Mean 2015-19 (%) | Outflow 2014-18 (%) | Inflow 2014-18 (%) | Geometric Mean 2014-18 (%) |
|---|---|---|---|---|---|---|
| Log Geog. Distance | 38.43 | 47.85 | 64.16 | 40.03 | 47.85 | 64.21 |
| Same State Dummy | 1.47 | 2.09 | 2.48 | 1.62 | 2.2 | 2.63 |
| Hist. Search Frictions Controls | 4.3 | 5.21 | 7.01 | 4.39 | 5.01 | 6.83 |
| Hist. Origin FE (2005) | 43.85 | 3.82 | 12.3 | 42.37 | 3.77 | 11.37 |
| Hist. Dest. FE. Adj. (2005) | 7.92 | 7.13 | 4.26 | 7.35 | 7.3 | 4.63 |
| Hist. Log Status Quo Bias (2005) | 4.03 | 33.88 | 9.79 | 4.23 | 33.88 | 10.33 |

Notes. 1. This table presents the Shapley Decomposition of the overall R2 of the six regressions in Table A14. 2. Six groups of control variables are used, including log geographic distance, the same state dummy, the three historical search frictions controls, historical origin fixed effects, historical destination fixed effects adjusted to reflect the counterfactual scenario where there is no status quo bias, and finally, the historical status quo bias estimate. 3. The historical fixed effects and status quo bias estimates are taken from the 2005 migration gravity regressions in Table A11, A12 and A13.