On Migration Gravity with Status Quo Bias and Job Search Friction*

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Abstract

This paper presents and estimates a search-theoretic model of mobility in a multiregional setting with status quo bias in locational preferences. The solution features a revised closed-form migration gravity equation and new structural interpretation to gravity estimates adjusted to accommodate involuntary unemployment. Using a collection of search friction proxies, we empirically test the model, and back out status quo bias estimates for US counties. We find that status quo bias estimates are spatially dispersed, and embody a wealth of non-wage individual and community profile cues, such as political orientation, religiosity and climate, that are correlated with the tendency to stay put.

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

JEL Codes: J61, J64, R23

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1 Introduction

A longstanding phenomenon in the U.S. labor market has been that of a persistently low and declining internal mobility rate (Basso and Peri, 2020; Molloy et al., 2011a, 2016; Dao et al., 2017) despite stark spatial disparities in unemployment incidence and wage differences. This level of persistence is puzzling particularly when social media as means to offset informational friction via interpersonal/group communications has been rapidly on the rise.[1] In this paper, we bring together search friction and status quo bias in locational preference within a unified setting of labor mobility. Conditional on job search frictions, to what extent is low mobility attributable to status quo biases in locational preference? Can status quo bias estimates unlock hitherto underappreciated factors, such as community-level political orientation, religiosity, and climate, that may come into play in migrants decision to leave or to stay?

By status quo bias, we refer to the spatial expected utility premium / discount a current resident attaches to her own location relative to a new immigrant (Faini and Venturini, 2001). The underlying sources of status-quo biases are many (Samuelson and Zeckhauser, 1988),[2] including for example prior investment in social capital, friendship and professional networks (Borjas, 1992), information asymmetries between residents and new migrants (Bryan et al., 2014), sunk investments (e.g. housing, schooling, adaptation to climate and local congestion) (Helderman et al., 2006), and cultural affinity and relationships with ethnic enclaves (Belot and Ederveen, 2012; Albert and Monras, 2017). These tendencies create asymmetric locational preference between current and new migrants that can influence mobility patterns.[3]

We develop and estimate a search theoretic model of inter-regional migration flows with search friction and status quo bias in locational preference. Thus, we depart from the canonical random utility model origins of the gravity equation with extreme value distributed preference idiosyncracies (Anderson, 2011; Bertoli and Fernández-Huertas Moraga, 2012), and adopt a setup with simultaneous multilateral Poisson job arrivals as a starting point.[4] In this setting, the frequency and origins of job arrivals depend on destination-specific job vacancies and the collection of job

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

[2] The diversity of these potential sources of status quo bias makes emphasizing any one of them a non-trivial modelling call. Our status quo bias term is specified therefore as an umbrella term that houses these diverse mechanisms. Our empirical sections will then use the status quo bias estimates to help reveal any central tendencies in the data.

[3] A related concept is home bias which more specifically refers to identity and childhood neighborhood / birth-place preference effects (Djajic and Milbourne, 1988; Kennan and Walker, 2011; Heise and Porzio, 2019).

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

search network links, including third-party linkages which govern the overall general equilibrium sizes of the job seeker pool in each destination – an important feature since 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 function. 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 local residence 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) dyadic search intensities to capture the strength of bilateral job and location information flow, (ii) origin- and destination-specific expected utilities of employment as push and pull forces, adjusted to account for spatial differences in status quo bias, unemployment, and the intensity of third-party links connecting a destination to all other sending locations, and (iii) a pair of (inward and outward) multilateral migration resistance terms, also adjusted to account for status quo bias.

Beyond allowing for status quo bias, the revised migration gravity equation sheds new light on the determinants of mobility. First, mobility depends on both bilateral and multilateral search friction. As such, universal improvements in communication technology is a double-edged sword, as information fosters connections between places both bilaterally and multilaterally – with better communication links everywhere, each improvement in bilateral ties is simultaneously challenged by a more competitive job market as the effective pool of job seeker expands everywhere. Thus, broad-based advances in communication technologies need not imply improvements in mobility (Basso and Peri, 2020; Molloy et al., 2011a, 2016; Dao et al., 2017).[5]

Second, the revised gravity equation clarifies how bilateral mobility co-moves with unemployment in equilibrium. The iconic population product term of the structural migration gravity equation, shown in Anderson (2011) in the context of migration based on random utility and no involuntary unemployment, requires a revision when search-friction induced unemployment is 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) destina-

[5]We also show that a reduction in status quo bias in any one location promotes population outflow, and add that a reduction in status quo bias everywhere, by contrast, can have the opposite effect on mobility between select locations whenever the multilateral impacts of status quo bias on job competitiveness dominates the improvement in any particular bilateral mobility link.

tion employment inclusive of all immigrants, which takes into account the unemployment shares in all third party sending locations. Since the unemployment rate is just the share of job seekers who fail to find a job anywhere, unemployment is both a driver, and is driven by the forces of migration.

Taken together, our setup predicts that mobility depends on status quo bias, typically unknown to the researcher, as well as a term that co-moves with migration, unemployment. This setting clarifies the biases that can come into play when estimating migration gravity without regard for these spatial differences. 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.[6] To control for job search friction we first account for spatial distances and border effects. Using the 1940 full-count Census records, we then construct three historic 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 friction 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 friction. 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.[7]

We furnish two applications of our empirical setup. First, we demonstrate the role of historic search friction controls on current inter-regional mobility in two different versions of the migration gravity setup. These include inflow shares migration gravity (inflow as a share of non-movers) and outflow shares migration gravity (outflow as a share of non-movers). In empirical applications of the gravity model, one readily finds a variety of examples including outflow gravity (e.g. Eaton and Kortum, 2002; Artuç et al., 2010), or geometric means of outflow and inflow gravity (e.g. Head and Ries, 2001). Guided by our model, we show that the effects of bilateral search in-

[6]Our data set has observations on county-to-country migration rates between 452 unique counties. In these 452 counties, there is a wide range of unemployment rates from 2.2% to 23.6%, while total outmigration and total immigration are also universally and simultaneously positive from 615 to over 32,000 and from 345 to over 23,000 respectively.

[7]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.

tensity on outflow and inflow gravity are similar regardless of whether inflow or outflow gravity is chosen. We also point out that while the search intensity coefficients have similar interpretations, the location fixed effects of outflow gravity, being ratios of expected utilities, have a relative expected utility interpretation. Meanwhile, location fixed effects of inflow gravity are functions of multilateral resistance terms, 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.[8] *A priori*, since origin and destination fixed effects absorb any county-level barriers to migration not accounted for by search friction controls, search related barriers to migration may be misattributed as status quo bias if relevant search friction controls are replaced by industry- or occupation-neutral barriers to migration, such as geographic distance.

Using our three historic dissimilarity indices and same state status as search friction controls, we find that status quo bias adds a 24.7% average expected utility premium, and a 0.3% median expected utility premium favoring current residents to stay. Put another way, close to half of the counties in our study do not exhibit status quo bias favoring their current county of residence. At the state-level, status quo biases estimated using historic search friction controls are diverse, with highest average (positive) premia in New York, Texas, California, Florida, and Minnesota. However if we we proxy for search friction only using distance and border effects without accounting for dissimilarity in ethnic, occupation and industry compositions, we see an over four-fold increase in the average estimated status quo bias at 89.1%, with a median of over 40.5%. At the state level, the rust belt states now harbor amongst the highest status quo biases. Thus, ethnic, occupation and industry composition dissimilarity explain a part of immobility that will otherwise be relegated to the umbrella term, status quo bias.

While these differences in state-level means and medians are notable, a key lesson to take away is that the choice of search friction controls matter since the status quo bias terms are estimated as a residual. Going beyond these estimated means and medians, we want to see if there are more general lessons that can nonetheless be learned from estimates across different search intensity controls. In particular, we correlate status quo bias estimates with a wide array county-

[8] 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.

level controls to ascertain visual patterns via heat maps, as well as least squares associations via Least Absolute Shrinkage and Selection Operator (LASSO). Interestingly, regardless of the precise combination of search intensity controls, we find that status quo bias estimates are systematically correlated with features of local economies that are often overlooked in migration gravity research, but related to job mobility based on skills, age, and other lived experiences. The latter includes investments to adapt to local conditions, preferences to live in a location with shared identity, and local ties that are only developed through interpersonal interaction and service, for example. In particular, we find that community-level profiles including climate, political orientation shares 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) in showcasing novel community-level correlates that strengthen the bonds that individuals attach to their own 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 of the determinants bilateral migration (Ramos, 2016).[9] Our work demonstrates that the gravity closed form can be preserved with the addition of search friction determinants, with helpful revised estimates interpretation (e.g. 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 historic search friction controls on migration and the importance of status quo bias, we demonstrate that mobility revises and is revised by the spatial spread of different types of job search network links across space and time, naturally implying path-dependence in general equilibrium outcomes when inter-regional mobility is part of the story (Chau, 1997; Kerr et al., 2017).

There is a nascent literature applying search friction models in spatial general equilibrium set-

[9] The literature has uncovered a host 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, 2016), language and cultural barriers (Belot and Ederveen, 2012; Adserà and Pytliková, 2015), to name a few.

tings (e.g. Schmutz and Sidibé, 2018; Heise and Porzio, 2019).[10] 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 his / her current employment state. These models 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. The key differences between these studies and ours is that by accommodating simultaneous random job arrivals from any number of destinations, our model is able to rationalize and replicate the gravity closed form, provide exact guidance on how to interpret inflow and outflow gravity estimates, and prove that location fixed effects, when appropriately compared, offer a status quo bias interpretation.[11]

Finally, mobility in our setup is driven by individual costs and benefits considerations conditional on origin- and destination-specific characteristics and individual preferences. Clearly alternative drivers abound, including mobility driven by a desire to be better positioned to access 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 to work out a static labor market equilibrium model of mobility with search friction and status quo bias. Doing so 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 friction 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 demonstrate, some of these alternative drivers, such as climate, congestion, proximity to family, are in fact embedded as correlates of our status quo bias estimates.

[10]Our migration with search friction induced involuntary unemployment setup 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.

[11]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.

3 Model

We consider the migration decisions of N_m number of job seekers in each of M locations with $N = \sum_{m=1}^{M} N_m$.[12] Let there be $v_n > 0$ number of employment vacancies in destination $n = 1, ..., M$. Search friction prevents job seekers in origin m from sampling all v_n number of jobs in destination n. The likelihood that a worker is met with $z_n = 0, 1, 2, ...$ offers is given by a Poisson distribution with parameter $\lambda_{mn} \geq 0$:

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

The job arrival rate λ_{mn} depends on (i) the search intensity of workers from m in n, $a_{mn} \geq 0$, (ii) the number of vacancies v_n, and (iii) the search intensity adjusted number of job seekers ($a_{kn}N_k$) from all M locations in n, $J_n > 0$, defined as follows:[13]

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

a_{mn} reflects the level of search intensity as practised by workers in m for jobs in n, facilitated for example by social / career networks, geographic barriers such as distance, and other institutional barriers such as state boundaries.[14] All else equal an increase in a_{mn} raises job arrival λ_{mn}. Naturally, an increase in search intensity in any other kn pairing, $k \neq m$ will have the opposite effect, as it raises the intensity of job competition in n with other job seekers. This rise in competition is reflected in a matching increase in the effective number of job seekers in n, $J_n \equiv \sum_k a_{kn}N_k$ as a_{kn} rises.

We assume that the utility of location n for a worker from m, accounting for wages and non-wage benefits such as amenities, is random and specific to each vacancy-worker match.[15] The probability distribution of this match-specific utility in location n, ω, 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 associated distribution function

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

[13] The specification in (1) satisfies adding-up, namely total job arrivals in all M locations add up to the number of vacancies since:

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

[14] We state λ_{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).

[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).

$F_{mn}(\omega) = F_n(\omega, 1 + b_n)$, $m \neq n$, 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 in migration preference exists if and only if $b_n \geq (<) 0$.[16]

To gain further insights, let $F_n(\cdot)$ assume a generalized Pareto distribution with parameter $\epsilon \in (0, 1)$ and $w_n \in (0, 1]$, for $\omega \geq 0$[17]

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

otherwise

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

where $w_n \in [0, 1]$ and $w_n/(1 + b_n)$ are shift parameters, while ϵ is a shape parameter. The expected values of ω associated with $F_n(\omega, 1)$ and $F_n(\omega, 1+b_n)$ are simply $w_n(1-\epsilon)^{-1} > 0$ and $w_n[(1-\epsilon)(1+b_n)]^{-1} > 0$ respectively. Thus, our status quo bias term b_n, if positive, gives the spatial expected utility premium that a local resident attaches to her origin relative to that of a new resident (Faini and Venturini, 2001). b_n can also be equivalently interpreted as the expected utility discount that a non-native resident applies to moving to n.[18]

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

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

$p_{mn}(\omega)$ is the probability that the highest utility job a worker finds is not better than ω.

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 offers remain in local residence as unemployed.

[16] Samuelson and Zeckhauser (1988) define status quo bias as a " tendency to adhere to status quo choices more frequently than would be predicted by the canonical model."

[17] The generalized Pareto as a distribution class is commonly used in extreme value theory (Balkema and de Haan, 1974; Coles et al., 2001). The familiar exponential distribution, and the Pareto distribution are examples of special cases.

[18] The sources of status quo biases are many (Samuelson and Zeckhauser, 1988), to include for example prior investment in social capital and connectedness to local friendship networks (Borjas, 1992), information asymmetries between residents and new migrants (Bryan et al., 2014), sunk investments (e.g. home, schooling) (Helderman et al., 2006), or relationships with ethnic enclaves and cultural affinity (Belot and Ederveen, 2012; Albert and Monras, 2017).

Substituting into F_{nn} and F_{mn}, the distribution of the highest offer for a worker from m in destination n is:

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

where $\mathbb{I}_{mn}$ is an indicator variable which takes on the value of 1 if $m \neq n$, and zero otherwise. (6) shows that the probability distribution $p_{mn}(\omega)$ of the best offer for a worker from m to n assumes the functional form of a generalized extreme value distribution function,[19] with parameters λ_{mn}, and $w_n(1+b_n)^{-\mathbb{I}_{mn}}$. Higher search intensity through better network connection, or a higher λ_{mn}, and a higher expected utility in n, through $w_n(1+b_n)^{-\mathbb{I}_{mn}}$, both give rise to a first order stochastically dominating change in the distribution of the best offer from n, all else equal.

3.1 The Decision to Migrate

Denote μ_{mn} as the probability that a worker from m finds that the best utility draw in n, ω_{mn}, to be more appealing that any other one of the $M-1$ locations's best offers, ω_{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 α_{mn} denote the status quo bias adjusted search intensity

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

where status quo bias' contribution to migration friction when $m \neq n$ is on display explicitly. Also let W_n denote the employment-adjusted expected utility of location n where

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

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

Now, by the law of large numbers, μ_{mn} represents the fraction of the workers in m who prefers location n to any of the other $M-1$ locations.[20]

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

The expression

$$O_m \equiv \sum_{i=1}^N \alpha_{mi}W_i$$

is the direct parallel of the outward multilateral resistance term, capturing outward mobility friction in the standard migration gravity equation and trade gravity equation (Anderson, 2011; Bertoli and Moraga, 2013).[21] In the current setting, O_m normalizes bilateral search intensity α_{mn} to account for the influences of all other locations on the relative desirability of n for workers in m.

Importantly, our analogue of the outward multilateral resistance term in migration gravity with search friction is a sufficient statistic for the equilibrium share of unemployed job seekers. To see this, note that the total number of employed location m workers is

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

The share of unemployed job seekers in location m – defined here as the fraction of workers in location m who looked for a job but did not find one – $u_m = 1-\sum_{n=1}^M \mu_{mn}$ is thus uniquely

[20] 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 λ_{mn} in (1), α_{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 $p_{mn}(\omega)$.

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

captured by outward multilateral resistance:[22]

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

(10) spells out the inter-regional roots of local unemployment. The stronger the total outward multilateral migration resistance, the higher will be the unemployment share.

Proposition 1. *Bilateral mobility rates from m to n, μ_{mn}, depends on (i) bilateral status quo bias adjusted search intensities α_{mn}, (ii) destination expected utility W_n, and (iii) an outward multilateral resistance term O_m:*

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

3.2 Structural Gravity

It is straightforward to express (9) as a structural migration gravity equation. Doing so can reveal migration and unemployment as co-moving outcomes of population stocks and employment aggregates. Thus, let $M_{mn} = \mu_{mn} N_m$ denote total migration, and $L_n = \sum_m M_{mn}$ as total employment in n, we have:[23]

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

where I_n is denotes multilateral resistance capturing inward migration friction impacting mobility for destination n, with

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

and symmetrically, outward multilateral can be expressed as

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

Thus, total migration between two locations depends on (i) bilateral status quo bias adjusted search intensity α_{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

[22]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 does not include inflows of migrants from other locations who constitute a part of the total labor force.

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

employment product is normalized by the overall employment level $\sum_i N_i(1-u_i)$.

Several observations are in order. First, (11) prescribes the product of a particular pair of population / workforce indicators as the determinant in our structural migration gravity equation, $N_m(1-u_m)$ and L_n. Of course unemployment is featured in both expressions. In $N_m(1-u_m)$, the number of employed sending location workers $N_m(1-u_m)$ (inclusive of outward migrants) applies, whereas in L_n, total labor supply in n (inclusive of inward migrants) $L_n = \sum_k \mu_{kn} N_k = \sum_k \alpha_{kn} W_n(1-u_k)N_k/O_k$ applies.

Second, consider the special case where the search intensity across all locations are symmetric $\alpha_{mn} = \alpha > 0$. In this case, bilateral mobility simplifies to[24]

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

Put simply, with universal symmetry in search intensity even after adjusting for status quo bias, the fraction of workers from m in all destinations will be 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 friction free counterparts, even though search friction 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:

[24]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 is can be simply expresed:

$$OI = \alpha$$

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

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

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 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 α_{mn} for the same reason. We have thus:

Proposition 2. *Symmetric proportionate improvements in search intensity has no impact on mobility as measured by bilateral migration as a share of destination n employment (M_{mn}/L_n), or as a share of total employment of workers native to the origin m ($M_{mn}/[N_m(1 - u_m)]$). Also, symmetric proportionate improvements in search intensity does not affect the unemployment share u_m.*

Proposition 2 speaks to the puzzling observation of a persistently low level of labor mobility in the US and elsewhere (Basso and Peri, 2020), despite advances in information and communication technology by leaps and bounds in recent decades, along with greater ease in long distance inter-personal communication assisted by electronic communication. Of course, in practice, improvement communication technology have had a skewed impact on different communities, with resulting implications on migration and unemployment that will change depending respectively on (9) and (10).

What remains to be fleshed out is the ways in which changes in search intensity impact unemployment, through its influence on mobility. In three applications below, we work step by step towards answering this question.

4 Two Applications

We now have an estimable model of migration gravity in which heterogeneous search intensity, α_{mn}, and location-specific employment-adjusted expected utility W_n, and the outward multilateral resistance term O_m are simultaneously featured. In the following applications, we examine empirically the role of search intensity on migration, the meaning of location fixed effects, and in turn how to back out the degree of status quo bias from migration gravity estimates.

4.1 Outflow Gravity and Inflow 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),[25] and consider the outflow of migrants as a share of workers who are left behind, henceforth outflow gravity. From equation (9)

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

Three sets of push and pull forces are featured in (17): (i) the relative search intensities a_{mn}/a_{mm},(ii) the ratio of destination and 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 $n \neq m$,

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

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:

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

The push and pull factors associated with inflow gravity are (i) the relative search intensities a_{mn}/a_{nn}, and (ii) relative employment rates $[(1-u_m)\ln(1/u_m)]\,/\,[(1-u_n)\ln(1/u_n)]$, and (iii) sta-

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

tus quo bias at destination n.

$$\ln \mu_{mn} - \ln \mu_{nn} = \ln a_{mn} - \ln a_{nn} + t_m - d_n, \tag{19}$$

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

There are two important takeaways. First, outflow gravity (μ_{mn}/μ_{mm}) and inflow gravity (μ_{mn}/μ_{nn}) are *symmetrically* dependent on the relevant search intensities ratios, α_{mn}/α_{mm} and α_{mn}/α_{nn}. Thus, both outflow and inflow gravity 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. It should be noted that the expected utility and employment interpretations of outflow and inflow gravity equation, noted in (18) and (19) above, have analogous counterparts in the canonical structural migration gravity model without unemployment (e.g. Anderson, 2011). We single this property out here as a first step towards leveraging estimated location dummies to back out location-specific status quo bias.

4.2 Status Quo Bias

To start, we note that each location $i = 1, ..., M$ in a migration gravity model appears both as a destination as well 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 and t_i), and once as a destination (D_i and d_i). Using notations developed for outflow and inflow gravity where location dummies have expected utility interpretations, and relative employment interpretations respectively (18, 19),

$$T_i - D_i = \ln(1 + b_i) = d_i - t_i. \tag{20}$$

Importantly, therefore, the difference between the destination and origin fixed effects, when $m = n$, gives an estimate of the status quo bias of each location $i = 1, ..., M$. This is possible using both the outflow gravity equation, and the inflow gravity equation.

By construction, b_i is the expected utility premium that individuals in i attach to staying put relative to a newcomer. A positive b_i naturally acts as a mobility barrier and discourages labor movement. 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. α_{ij}, and hence outward gravity from i to j is decreasing in b_j.[26] Our task here is to separately tease out b_i from α_{ij}.

5 Data and Methodology

We collect data on bilateral county population flows from the 2014-2018 American Community Surveys. The dataset contains yearly counts of individuals who have moved between counties. Since migration is censored for small counties to avoid privacy concerns, we have observations on 425 unique counties. Three different types of bilateral connections guide our measurement of bilateral search friction. 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 receiving county n as

$$d_\ell(m, n) = \sum_{k_\ell \in K_\ell} (s_{k_\ell m} - s_{k_\ell n})^2 \in (0, 1), \quad \ell = eth, occ, ind \tag{21}$$

where ℓ is a member in a class of three search friction controls, including U.S. historic (1940) ethnic origin (eth), occupation (occ), or industry-of-employment (ind). K_ℓ is the set of all available groups within search friction control ℓ and $s_{k_\ell m}$ is the population share of a specific group k_ℓ in county m in 1940. We use the 1940 sample because it is a full-count historic data set providing detailed and complete coverage of county compositions across multiple dimensions.[27] By definition,

$$d_\ell(m, m) = 0 = d_\ell(n, n).$$

Since our search friction variables are based on historical county-level differences, it is instruc-

[26] 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 α_{ij} does.

[27] 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. The occupation and industry-of-employment distance measures, in turn, are based on Census definition of major occupation groups and industry groups.

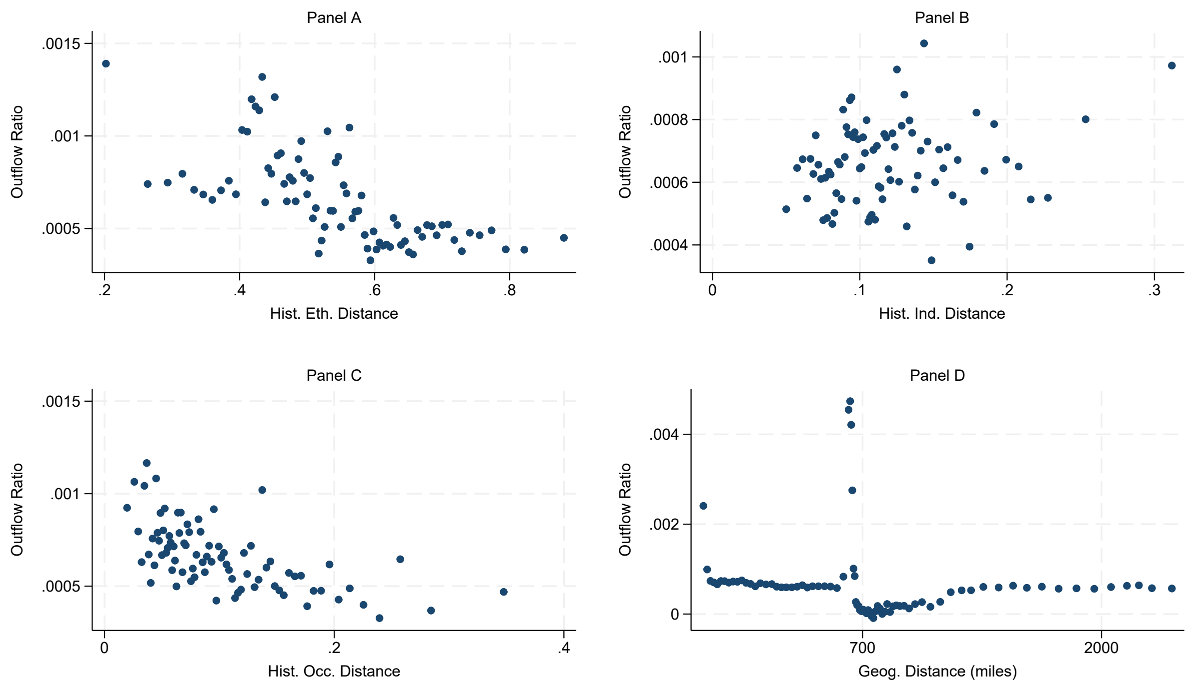
tive to visualize how these bilateral differences are related to migration flows. Figure 1 displays residualized binscatter plots of bilateral outflow ratio (μ_{mn}/μ_{mm}) on ethnic composition difference, industry-of-employment composition difference and occupation composition difference respectively controlling for same state status between county-pairs on mobility and search friction. The corresponding figures for inflow ratios are similar and relegated to the appendix. In Panel A, for example, counties that are historically more ethnically distant continue to exhibit less mobility today (more than 70 years later) even after controlling for same-state status. 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), McKenzie and Rapoport (2007), Mayda (2010), Blumenstock et al. (2019)). Since historic ethnic distance is arguably exogenous to current migration flows, we use historic ethnic distance as our first search friction control.

Panels B and C show the other two search friction indicators respectively based on historic 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 B and C in Figure 1 display residualized binscatter plots of the raw data relationship between bilateral outflow ratio and historic industry-of-employment distance and historic occupation distance. A negative relationship is indicative of the tendency for historic economic links to continue to have an impact on today's mobility.[28]

Finally, Panel D in Figure 1 shows the relationship between outflow ratio and distance (in miles) once again controlling for same-state status. Here too, we observe a general downward sloping relationship. Nonetheless, the pattern appears discontinuous with a notable U-shaped relationship for relatively far away county pairs. The discontinuity begins at around 700 miles mark, which makes sense since this is close to the difference between the average distance between within-state county pairs (140 miles) and different state county pairs (950 miles). Thus, some of the highest mobility tend to occur between geographically proximate counties, particularly those

[28] Historic economic links between location may affect today's migration via its effect on current economic linkages if these characteristics are slow to change, or by giving rise to social networks and friendship connections over time that have lasting effects, or both. We turn to these possibilities in Section 7.

Figure 1: Binscatter Plots of Population Outflow Ratios and Search Intensity Controls



Notes. 1. This figure presents binscatter plots of the relationship between U.S. county level population outflow ratio (bilateral population outflow / total non-movers at source, 2014-2018 average, ACS) and search intensity controls. 2. Historic ethnic distance is constructed according to equation (21) 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 historic occupation composition difference is similarly constructed according to equation (21) using historical (1940) industry and occupation composition shares. 4. Geographic distance is the distance between county pairs. 5. Same state status between counties are used as controls.

within the same state. The discontinuity and subsequent U-shaped pattern is consistent with high mobility rates between counties that are closed together but not in the same state, as well as a relatively high mobility for coast to coast county pairs as well.

For outflow gravity, we estimate the following gravity equation:

$$\ln\left(\frac{\mu_{mn}}{\mu_{mm}}\right) = \ln\left(\frac{a_{mn}}{a_{mm}}\right) + D_n - T_m + \varepsilon_{mn}, \tag{22}$$

and analogously for inflow gravity, we estimate:

$$\ln\left(\frac{\mu_{mn}}{\mu_{nn}}\right) = \ln\left(\frac{a_{mn}}{a_{nn}}\right) + t_m - d_n + \epsilon_{mn}, \tag{23}$$

where μ_{mn} is the ratio of the number of workers from m to n to the number of non-movers in m with employment. The pair of variables D_n and T_m in equation (22) and t_m and d_n in equation (23) 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}/a_{mm}, we assume that $\ln a_{mn}/a_{mm}$ is a linear combination of our list of bilateral search intensity controls, together with distance and same state dummy:

$$\ln\left(\frac{a_{mn}}{a_{mm}}\right) = \sum_{\ell=eth,occ,ind} \gamma_\ell^o \ln d_\ell(m,n) + \gamma_{dis}^o \ln dist_{mn} + B_{mn}^o,$$

and

$$\ln\left(\frac{a_{mn}}{a_{nn}}\right) = \sum_{\ell=eth,occ,ind} \gamma_\ell^i \ln d_\ell(m,n) + \gamma_{dis}^i \ln dist_{mn} + B_{mn}^i,$$

where γ_ℓ^o and γ_ℓ^i denotes the intensity of the influence of our search friction controls on the search intensity ratio for outflow and inflow gravity respectively. γ_{dist}^o and γ_{dist}^i are the corresponding coefficients for geographic distance and B_{mn}^o and B_{mn}^i are the same state fixed effects in the two settings. Finally, ε_{mn} and ϵ_{mn} are respectively functions of source-destination-specific shocks unrelated to search frictions that affect migration, some of which may be unobservable.

The average county in the data has 53 observable outward migration links, out of a possible 424. This feature is not uncommon in migration data (e.g. Beine et al. (2011), Beine et al. (2016)). Two solutions have been adopted so far. These include a 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 censored due to privacy concerns, rather than actual zeros. Meanwhile, a count regression approach does not work in our case either, since our main estimation equations (18 and 19) present ratios of labor flows, rather than number of migrants.

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. By the same token, 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 (20) – 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. The same approach is adopted in Bailey et al. (2018) in the context of migration, and Eaton and Kortum (2002) in the context of the gravity of international trade, among others.

6 Results

In this section, we provide empirical estimates of the determinants of county-level bilateral migration, status quo bias as well as unemployment, using regression specifications guided by the two applications of our model.

6.1 Migration Gravity Estimates

The first three columns of Table 1 reports OLS estimates of the effect of log search friction controls on log outflow ratios. Robust standard errors clustered at the origin and destination county levels are included. In column 1, the estimates show that the correlations between log historic search friction and log outflow ratio are statistically significant at the 1% level and negative. All three of our search friction proxies show up as statistically significant obstacles to migration. This negative relationship holds even after controlling for same state status, suggesting that both historic ethnic and historic jobs related economic linkages are important determinants of today's migration pattern. Our findings regarding the role of historic ethnic differences 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).

Complementing ethnic networks as a source of migration path dependence over time, the findings here confirm two additional sources of migration path dependence that work through economic linkages, which favors the mobility of workers between historically similar hubs of economic activities measured in terms of industry and occupational composition. Between industry-of-employment and occupation connections, the industry-of-employment effect is stronger. Thus, migrants have a stronger tendency to fall back on places that share common industry compositions, more so than places that share task-related occupation similarities, given the same change in dissimilarity assessed in equation (21).

In column 2, we replace the search friction controls with the log distance in miles, effectively using geographic proximity as an alternative search friction proxy, once again controlling for same-state status. As expected both controls are statistically significant at the 1% level, and the same-state dummy is positive while the distance coefficient is negative. These suggest that all else equal, cross-state migration is significantly more challenging than within-state migration, and likewise, long distance migration is more challenging than movements nearby. In column 3, we combine search friction and geographic proximity controls and the results are qualitatively similar.

6.2 Status Quo Bias Estimates

Levels and Distribution

From equation (20), status quo bias at a given location can be inferred from the corresponding estimated origin and destination fixed effects. Using county-level origin and destination fixed effects estimates in Table 1, we report the corresponding status quo bias estimates in Table 1. In column 1, using the three historic search friction proxies, we find county residents on average put a 24.7% expected utility premium on their existing location of residence relative over the expected utility assessments of new movers. The distribution of status quo bias is skewed to the right, with a median status quo bias at around 0%, implying that the share of counties that do not put a positive premium on staying in their existing locations relative to the share of those that do is about 50-50. In column 2 where we replace the historical search friction proxies with log distance, the associated status quo bias terms are substantially larger, averaging at 89.1% with median at 40.5%. In column 3, we include all search proxies and the resulting estimates are in between that of columns 1 and 2. Because of outliers, we also present 1% winsorized status quo bias estimates. Doing so reduces the mean status quo bias estimates from 24.7% to 22.2% with historic search friction proxies as controls, and from 89.1% to 40.5% with geographic distance control.

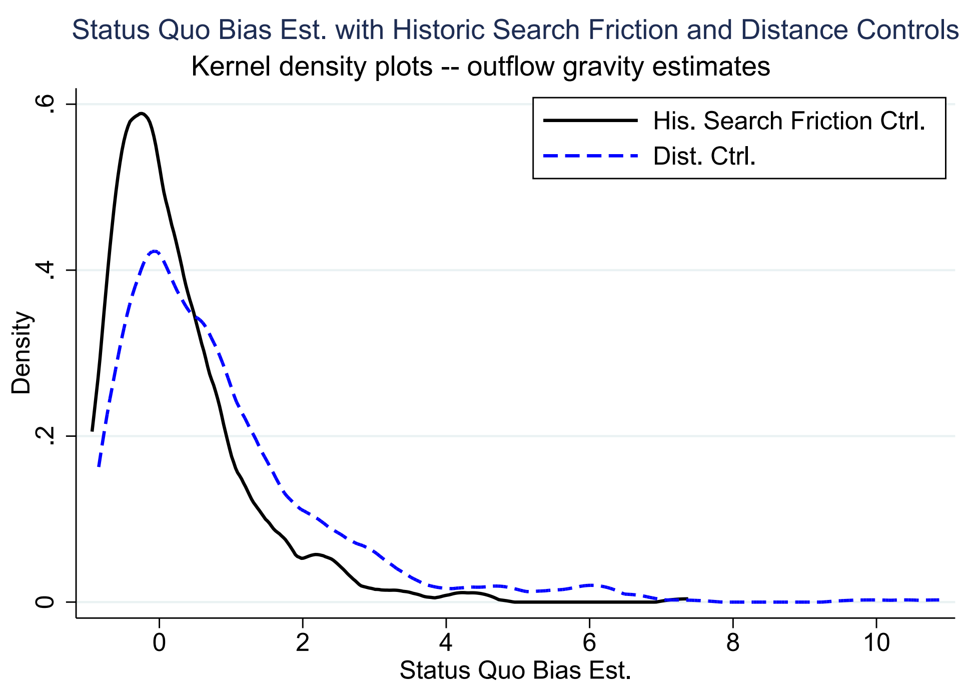
Status quo bias estimates are dispersed. To show the distribution of these estimates, Figure 2 plots the kernel density distribution of status quo bias estimated based on column 1 and column 2 estimates in Table 1 respectively. The figure shows two right-skewed distributions, with status quo bias estimated with historical search friction proxies only having higher density around smaller values. To look at status quo bias dispersal in spatial terms, we aggregate county-level status quo bias terms using column 1 (Table 1) status quo estimates to the state-level and illustrate the resulting state-level pattern in Figures 3a and 3b.

Evidently, status quo bias is highly heterogeneous across states as well, but once again, the choice of search friction controls plays an important role. In Figure 3a, using historic search friction controls, status quo bias estimates are highest in New York, Texas, Florida and California. In Figure 3b, status quo bias estimates are generally higher, and without controlling for historic economic linkage, the rust belt states now share some of the highest levels of status quo bias. Table 4 displays the list of counties in California, Florida, New York and Virginia and District of Columbia with the highest and the lowest estimated status quo bias. These show in a nutshell that spatial heterogeneity in status quo bias is both a cross-state, and a cross-county within state phenomenon.[29] These observations reiterate the relevance of historic social and economic linkage proxies as determinants of current mobility, without which observed relative immobility will be mis-attributed as a preference bias in favor of the status quo particularly in the manufacturing hub states.

Since status quo bias contrasts expected utility assessments between individuals with lived experiences in a location compared to newcomers, one would expect that the extent of the bias should be correlated with demographic, skills, and community-level cohesiveness considerations

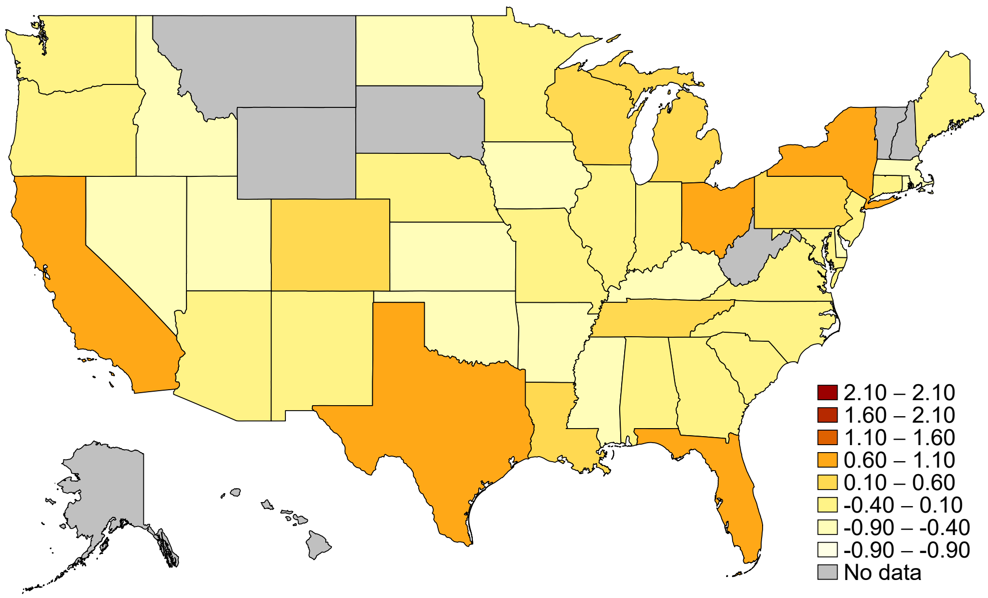
[29] In Table 4, we find that well-known dense urban centers, such as New York, San Francisco, Washington D.C., and its surrounding Virginia counties have the lowest status quo biases. Meanwhile, there are large number of surrounding counties in these states with high status quo biases such as Schenectady county (NY), Napa county (CA), for example, in addition to a number of counties in Florida such as Indian River and Marion. The latter list tend to be less active as hubs of economic and / or manufacturing activities.

Figure 2: County-Level Status Quo Bias (b_n) Dispersion (Outflow Gravity).

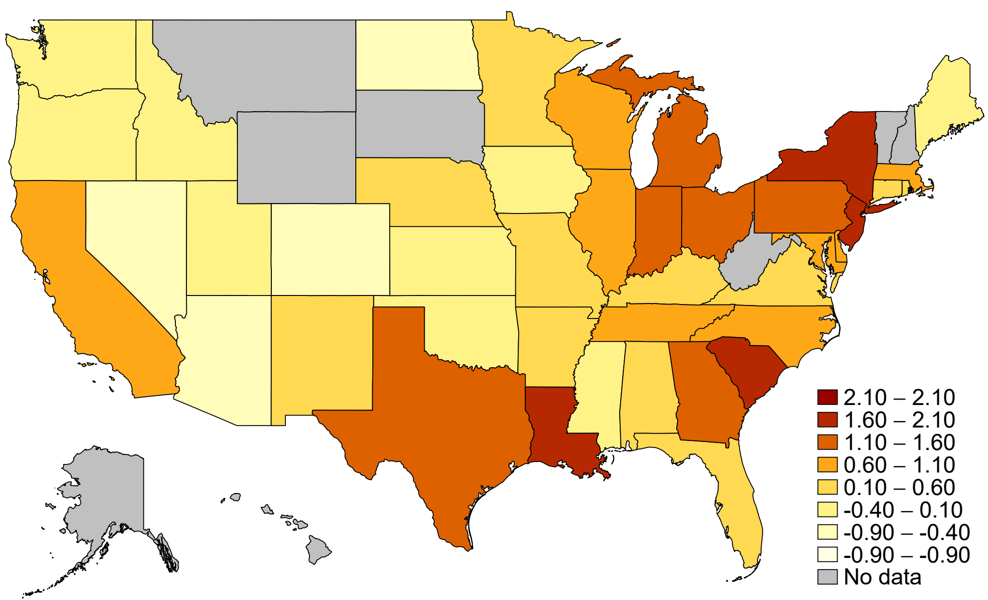


Note: This figure displays kernel density estimates of status quo bias b_n based on OLS outflow gravity regressions in columns (1) and (2) of Table 1 with robust standard errors clustered at the origin and destination county levels.

Figure 3: The Geography of Average State-Level Status Quo Bias (Outflow Gravity)



(a) State-Level Status Quo Bias Using Historic Search Friction Controls



(b) State-Level Status Quo Bias Using Geographic Distance Control

Notes. 1. Figure 3a displays state-level average status quo bias (b_n) estimated based on OLS outflow gravity regressions in columns (1) of Table 1. 2. Figure 3b displays state-level average status quo bias (b_n) estimated based on OLS outflow gravity regressions in columns (1) of Table 1.

that impact the decision and the ease of mobility. 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), for example.

To aid visualization of these possible drivers of status quo bias, we provide heat maps of our status quo bias estimates (columns 1 and 2 in Table 1) respectively using historic search friction and distance as gravity controls. In Figure 4a, the heat map demonstrates stage of life triggers of status quo bias by jointly illustrating county-level fractions of individuals who live alone, and mean maximum January temperature. The fraction of individuals living alone is highest amongst older aged individuals (Roberts et al., 2018), while warmer winter temperatures is a popular indicator of their associated climate preference (Schmith Conway and Houtenville, 1998). We see that darker shades – stronger status quo bias based on columns 1 and 2 of Table 1 – are associated with counties with a higher fraction of individuals living alone, and a higher mean maximum January temperature. Figure 4b addresses community-ties drivers of status quo bias by bringing together religiosity, political preferences and our estimated status quo bias. As shown, counties with high adherence to the Catholic faith, and counties with a high Republican vote share are both associated with a higher degree of status quo bias.

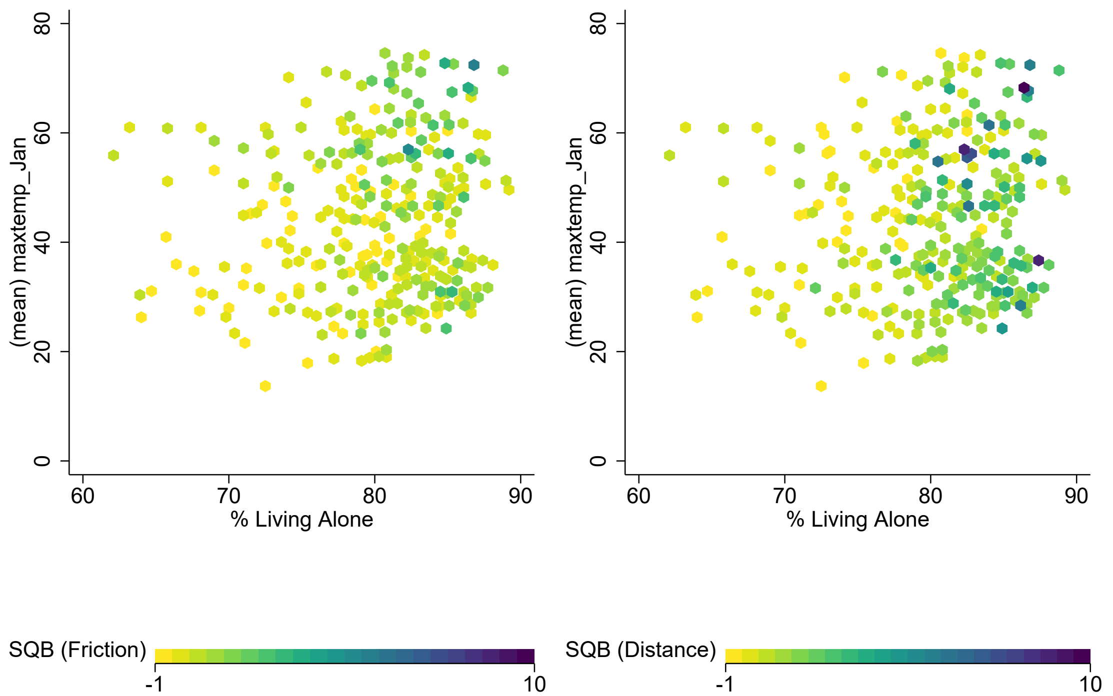
To complement status quo bias correlates related to stage of life considerations and community ties indicators of a preference to stay put, it is also possible that status quo bias is lower among communities with more individuals for whom immobility implies a higher opportunity cost (e.g. Machin et al., 2008; Molloy et al., 2011b). Figure 4c shows the relationship between status quo bias estimates and county-level fraction of working age (20-54) population, and fraction of individuals with a Bachelors degree or more. As may be expected, a lower status quo bias prevails in counties with more working age population and those with more individuals who are college educated.

We now further unpack the correlates of our estimated status quo bias terms. In particular, 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

Figure 4: The Correlates of Status Quo Bias Estimates (Outflow Gravity)

f

(a) Status quo bias, Environmental Considerations and Family Support



(b) Status quo bias, Community-Level Political Orientation and Religiosity

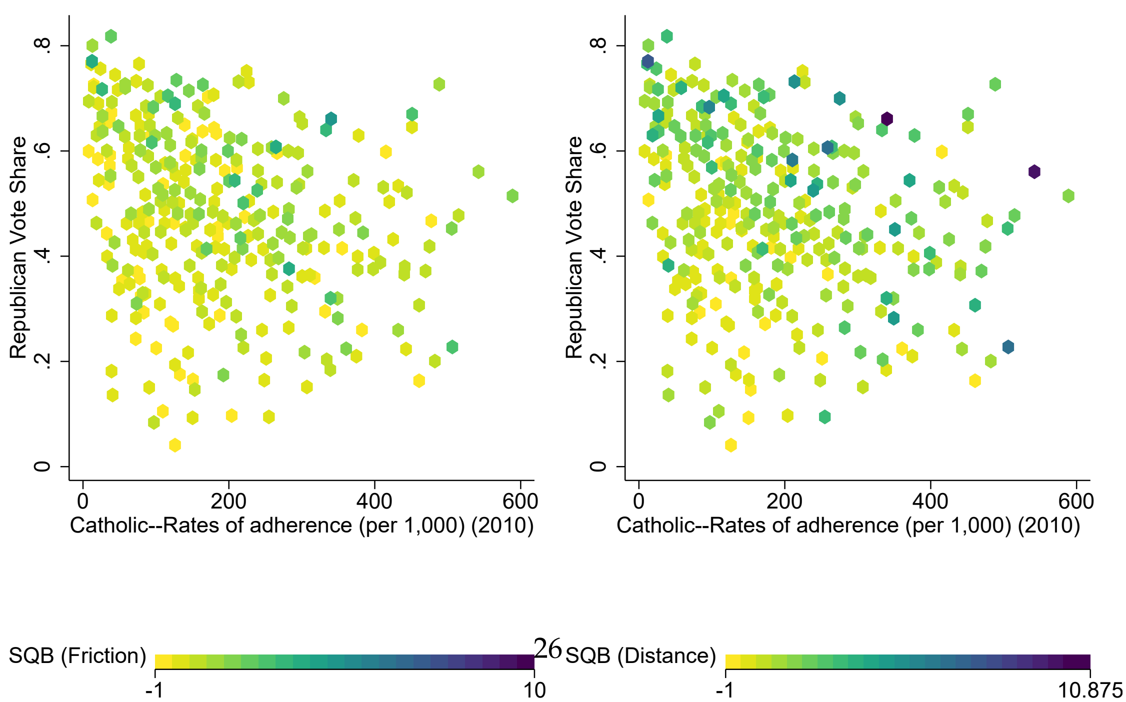
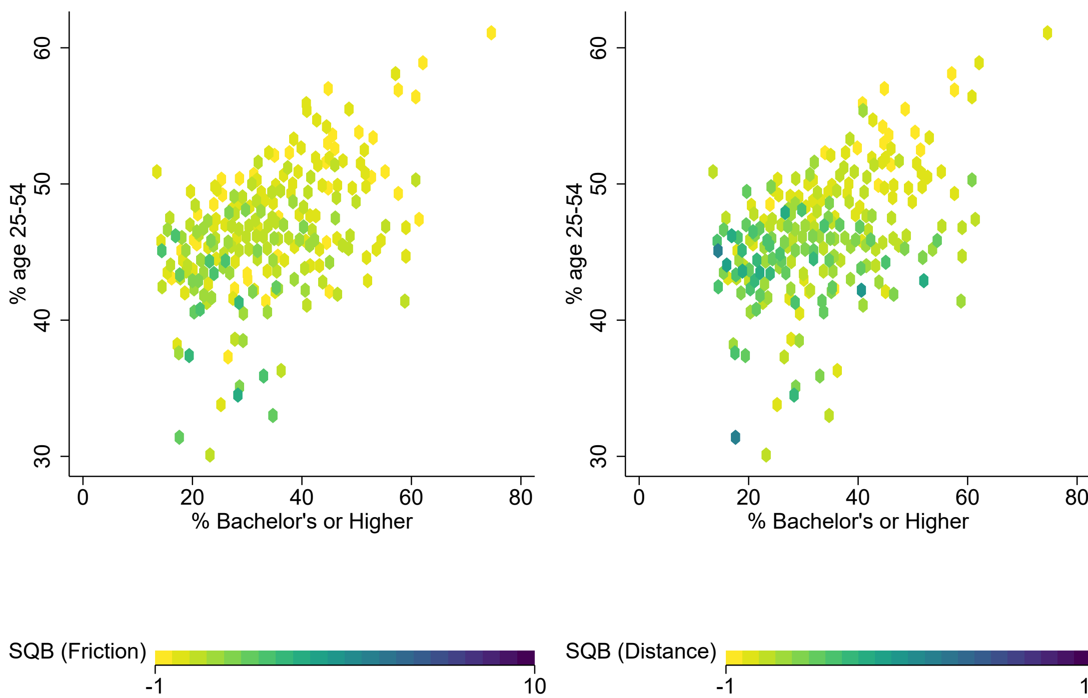


Figure 4: The Correlates of Status Quo Bias Estimates (Outflow Gravity, continued)

(c) Status quo bias, Working Age and College Educated Population



Notes. 1. This figure presents heat plot visualizations of the raw data relationships between status quo bias estimates and three sets of correlates. 2. SQB (Friction) denotes status quo bias estimates based on the outflow gravity regression in column 1 of Table 1 using historical search friction controls only. 3. SQB (Distance) denotes status quo bias estimates based on the outflow gravity regression in column 2 of Table 1 using geographical distance. 4. Shades of color indicate levels of estimated status quo bias in the corresponding cells. 5. Figure 4a plots the relationship between maximum mean temperature in January and county-level share of population living alone. 6. Figure 4b plots the relationship between county-level Repubican vote share and the rate of adherence to Catholicism (per 1000 population) in 2010. 5. Figure 4c plots the relationship between county-level share of working age population (between 20-54) and the share of population with a Bachelor's degree or above.

attributes.[30] 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 2 reports the significant correlates of status quo bias estimated selected by LASSO based on column 1 outflow gravity estimates in Table 1 using historic search friction proxies. 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 reflects the intuition behind Figures 4a, 4b and 4c quite well, indicating the importance of age, skill, and community level religiosity and political leanings regardless of the precise search fiction control. In addition to these features, Table 2 also shows that status quo bias is highly positively correlated with county-level congestion forces such as commute time and population density. This suggests that new migrants put a higher weight on the disutility of congestion and commute time than local residents in determining locational choice. This is consistent with asymmetric perceptions about the cost of living 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. Gender ratios features prominently also and may be telling a similar story related to congestion externalities associated with urban living, for U.S. counties with higher shares of males tend to be less urban. Controlling for age, we also find status quo bias to be positively correlated with warmer climate. This may be reflective of climate adaptation investment that constitute sunk costs (e.g. housing) and thus not readily moveable. People may also have asymmetric understanding about living conditions in warmer climates until they have lived experiences.

These lessons are a useful reminder that spatial heterogeneity in living standards extend well beyond wages and job prospects. The correlates of our status quo bias estimates included demographic profiles, community-level religiosity and political characteristics, congestion forces, as well as climate. Naturally, different population subgroups (by skills, gender, and birthplace, say) may value these features differently, and there may be other predictors of status quo bias in locational preferences. A more disaggregated status quo bias estimates at the population subgroup level can be obtained by leveraging bilateral migration data at the subgroup level.

[30] See Table A1 for a complete list of the variables.

7 Validation and Discussion

Inflow Gravity Regression. Our model predicts that status quo bias estimates should be similar whether based on outflow or inflow gravity estimates (equations (22) and (23)). We validate this prediction in columns 4 - 6 of Table 1, where search friction coefficients on inflow and outflow ratios share the same signs. They are similar in magnitude as well across regressions conditional on the set of search friction controls compared to columns 1 - 3 estimates in Table 1. Appendix Figure A2 shows the kernel density plots of status quo bias estimates from the two regressions, and Appendix Figures A3a and A3b show the state-level differences in average status quo biases. Evidently, these plots all show similar patterns across outflow and inflow ratio regressions.We also provide heat plots of status quo bias using inflow gravity estimation, where age, academic degree, religiosity and political orientation are correlated with status quo bias (Figure A4a, A4b and A4c). Finally, Appendix Table A2 provides the LASSO estimates of the significant correlates of our status quo bias estimates, and these are qualitatively similar to those obtained with outflow gravity estimates.

Mechanism of Historic Links on Current Mobility. What exactly do the three search friction proxies measure? Could it be that the search friction controls used in this study matter because they are correlated with the actual cost of migration, but not any job search related information advantages of bilateral connections? Since we have no individual-level informaion about whether each move is because of referrals from a friend, or assistance from a network of professional colleagues, we cannot directly assess this question, although of course 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)).

As an alternative approach to validate the mechanism that connect historic search friction 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.[31] The SCI is constructed using the total number of Facebook friendship

[31] 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.

links between individuals located in a pair of counties: for every county pair m and n

$$SCI_{mn} = \frac{\text{Facebook Connections}_{mn}}{\text{Pop}_m \text{Pop}_n}, \tag{24}$$

where Facebook Connections is the number of Facebook friendship links and POP is county population.[32] Bailey et al. (2018) normalizes the index such that the maximum value of the index 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, as demonstrated in Bailey et al. (2018) and Bailey et al. (2020). To our knowledge, with its 239 million users, the Facebook dataset is the only dataset that provides a comprehensive coverage of friendship networks at the national level in the United States. Figure A5 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 friendship networks on the U.S. coasts but also parts in the Midwest and the South.

First, we graph the relationships between historic search friction proxies and the SCI. To absorb county-specific difference related contributors to the SCI, we plot the relationship between search friction proxies and the SCI ratio, SCI_{mn}/SCI_{mm}. Figure 5 displays residualized binscatter plots of the SCI_{mn}/SCI_{mm} ratio, henceforth the SCI ratio, on ethnic composition difference (Panel A), industry-of-employment composition difference (Panel B) and occupation composition difference (Panel C) respectively controlling for same state status between county-pairs as in Figure 5. We note that there is a general negative relationship between the SCI ratio and our search friction proxies. To the extent that the SCI is a measure of the intensity of online information sharing and opinion exchanges, the patterns shown in Figure 5 are indicative of historical connections, whether through ethnic or economic links, that are persistent through time. Furthermore, since Facebook connections are voluntary links between "friends", the pictures in Figure 5 also suggest that the *nature* of the ties (social or economic) can change over time, for example translating yesterday's jobs related connections to social media "friends" today. In Panel D, we provide the residualized binscatter plot of the SCI ratio and distance (in miles), absorbing same state status. We see a generally negative, and discontinuous relationship with an inverted U for long distance cross-state county-pairs. This is consistent with the fact that social media connections are rife among

[32]Note: this variable is slightly 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.

counties that are popular migrant origins / destinations of one another.

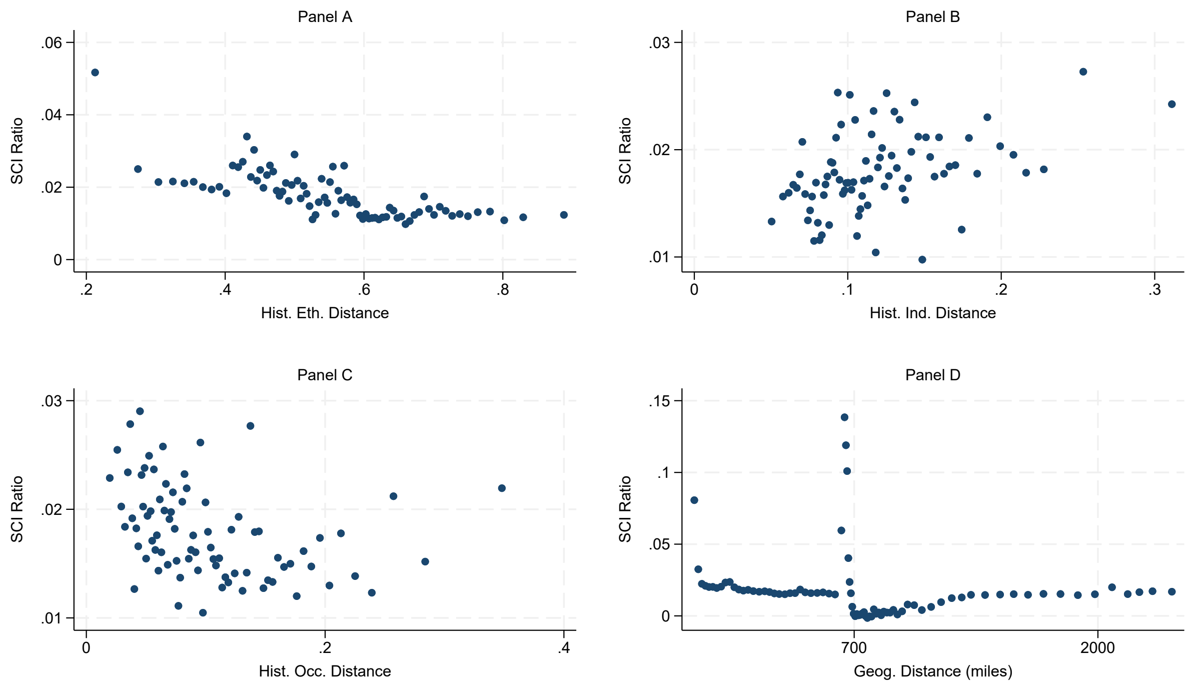
Finally, we conclude this section with an OLS regression of the SCI ratio for county-pairs and the correlation with the search friction proxy, distance and same-state status. Table 3 summarizes the results. As expected based on the relationships already shown in Figure 5, current scope for information exchange via social media connection is driven by historic ethnicity and economic links. The relationships are negative and statistically significant. Like in inflow and outflow ratio regressions, ethnicity and industry-of-employment ties play stronger roles compared to occupational ties. These complement geographic distance and same state status to provide a fuller picture of the contributors to the underlying drivers of the intensity of information exchange between county pairs.

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 or inflow 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.

With this setting, we provide answers to the question we posed at the outset of this paper: Is labor mobility is too low? 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 of search friction, we make three key observations. First, status quo bias estimates are sensitive to the introduction of search friction controls. We find that historic economic linkages as search friction proxies significantly reduce the size of the estimated status quo bias, particularly in manufacturing hubs such as the rust belt. Second, status quo bias is dispersed, both between states, and between counties within states. Thus, state level averages only tell the story with a partial view. Finally, status quo bias estimates are well-explained by a list of factors that indicate the importance of stage- and types-of-career characteristics, family- and community-level shared

Figure 5: Binscatter Plots of Facebook Social Connectedness Index and Search Intensity Controls



Notes. 1. This figure presents a binscatter plots of the relationship between the Facebook Social Connectedness Index and search intensity controls. 2. Historic ethnic distance is constructed according to equation (21) 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 historic occupation composition difference is similarly constructed according to equation (21) using historical (1940) industry and occupation composition shares. 4. Geographic distance is the distance between county pairs.

identity, environmental adaptation, congestion externalities and family-support considerations. These factors are indicative of personal- and community-level considerations involving sunk investment, and revelations via lived experiences that go beyond traditional cost-benefit evaluations of the need for mobility. The lessons here allow for a deeper dive into the determinants of mobility / immobility, which include a combination of economic drivers tightly intertwined with individual and community locational preferences. Such considerations offer rich contexts for future research on labor mobility, to complement a growing literature that have incorporated a diversity of non-wage determinants of the gravity of migration.

Table 1: Determinants of Population Outflow and Inflow Ratios and Status Quo Bias Estimates

	(1) Outflow	(2) Outflow	(3) Outflow	(4) Inflow	(5) Inflow	(6) Inflow
Ln Hist. Eth. Distance	-0.606***		-0.448***	-0.617***		-0.458***
	(0.047)		(0.038)	(0.047)		(0.039)
Ln Hist. Ind. Distance	-0.614***		-0.393***	-0.593***		-0.372***
	(0.087)		(0.075)	(0.088)		(0.076)
Ln Hist. Occ. Distance	-0.091***		-0.094***	-0.111***		-0.116***
	(0.026)		(0.028)	(0.026)		(0.027)
Same State Dummy	1.312***	1.159***	0.505***	1.333***	1.199***	0.533***
	(0.090)	(0.057)	(0.077)	(0.092)	(0.057)	(0.077)
Ln Geog. Distance		-0.692***	-0.658***		-0.692***	-0.657***
		(0.022)	(0.022)		(0.022)	(0.022)
Observations	22281	22281	22281	21701	21701	21701
Mean dep. var.	-8.755	-8.755	-8.755	-8.781	-8.781	-8.781
R2	0.552	0.624	0.636	0.568	0.637	0.650
Median status quo bias	0.003	0.430	0.465	0.009	0.483	0.480
Mean status quo bias	0.247	0.891	0.814	0.245	0.940	0.856
Winsorized mean status quo bias	0.222	0.405	0.382	0.189	0.396	0.368

Notes. 1. Columns 1 - 3 of this table displays the relationship between U.S. county level population outflow ratio (bilateral population outflow / total non-movers at source, 2014-2018 average, ACS) and search intensity controls. 2. Columns 4 - 6 of this table displays the relationship between U.S. county level population inflow ratio (bilateral population inflow / total non-movers at destination, 2014-2018 average, ACS) and search intensity controls. 3. Three search friction controls are included: "His. Eth. Distance", "His. Ind. Distance", "His. Occ. Distance", "Geog. Distance", and "Same State Dummy" respectively refer to historic ethnic composition difference, historic industry-of-employment composition difference, occupation composition difference defined in (21), geographic distance, and same-state status. 4. Status quo bias estimates (SQB) are calculated based on equation 20. 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 2: Predictors of Status Quo Bias (Outflow Gravity Estimates)

Status Quo Bias Estimates (His. Search Friction Controls)	Coefficients (Outflow Gravity)	Status Quo Bias Estimates (Geographical Distance)	Coefficients (Outflow Gravity)
Maximum January temperature	0.202	% living alone	0.176
% drive alone	0.161	Republican Vote Share	0.147
% housing built between 1990 and 1999	-0.161	% divorced	-0.146
Log population density	0.145	% males	-0.112
% aged between 20 and 54	-0.136	% aged between 20 and 54	-0.108
% commuters	-0.114	Log avg. commute time	0.103
% Hispanic	0.097	% housing built 2010 or later	-0.103
% Bachelors or more	-0.094	% Bachelors or more	-0.086
% living alone	0.077	% housing built between 1980 and 1989	-0.083
July precipitation	-0.061	% with children	0.081
% housing built between 1950 and 1959	0.059	Log population density	-0.072
Maximum July temp	-0.058	Heat Days	0.065
Republican Vote Share	0.056	% Hispanic	0.038
% housing built between 1960 and 1969	-0.047	% housing built between 1940 and 1949	0.037
% Evangelical	0.046	%Catholic	0.032

Note: This table lists the top 15 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 A1

Table 3: The Facebook Social Connectedness Index, Historic Search Friction, and Geographic Distance

	(1) OLS	(2) OLS	(3) OLS
Ln Hist. Eth. Distance	-0.600***		-0.444***
	(0.039)		(0.029)
Ln Hist. Ind. Distance	-0.461***		-0.243***
	(0.063)		(0.050)
Ln Hist. Occ. Distance	-0.032*		-0.035*
	(0.019)		(0.019)
Same State Dummy	0.997***	0.853***	0.204***
	(0.074)	(0.042)	(0.056)
Ln Geog. Distance		-0.675***	-0.646***
		(0.019)	(0.020)
Observations	22281	22281	22281
Mean dep. var.	-5.205	-5.205	-5.205
R2	0.780	0.880	0.893

Notes. 1. This table displays the relationship between the Facebook Social Connectedness Index and search intensity controls. 2. Three search friction controls are included: "His. Eth. Distance", "His. Ind. Distance", "His. Occ. Distance", "Geog. Distance", and "Same State Dummy" respectively refer to historic ethnic composition difference, historic industry-of-employment composition difference, occupation composition difference defined in (21), geographic distance, and same-state status. 3. County-origin and county-destination fixed effects are included. 4. Robust standard errors clustered at the origin and destination county levels in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: County Rankings: Top 10 and Bottom 10 Degree of Status Quo Bias (Select States)

Bottom 10 Status Quo Bias Counties

California			**Florida**			**New York**			**Vriginia / DC**		
County	SQB	Ln Pop Density	County	SQB	Ln Pop Density	County	SQB	Ln Pop Density	County	SQB	Ln Pop Density
Kings	-0.50	-1.19	Alachua	-0.49	-0.39	Tompkins	-2.14	-0.61	District of Columbia	-1.90	2.73
Santa Clara	-0.47	1.07	Leon	-0.33	-0.03	New York	-1.21	4.09	Newport News city	-1.68	1.09
San Francisco	-0.46	1.88	Santa Rosa	-0.22	-0.93	Chautauqua	-0.63	-1.38	Arlington	-1.56	2.62
Imperial	-0.23	-2.04	Escambia	-0.17	-0.15	Oswego	-0.45	-1.33	Alexandria city	-1.39	2.73
Butte	-0.13	-0.99	Orange	-0.15	0.97	Bronx	-0.22	3.52	Richmond city	-0.53	1.84
Merced	-0.12	-0.98	Okaloosa	-0.08	-0.72	Kings	-0.22	3.58	Hampton city	-0.47	0.73
San Luis Obispo	-0.02	-1.47	Osceola	-0.04	-0.55	Albany	0.21	0.26	Virginia Beach city	-0.25	0.65
Yolo	0.12	-0.61	Collier	0.07	-0.86	Dutchess	0.29	-0.15			
San Diego	0.19	0.47	Hillsborough	0.30	0.81	Monroe	0.33	0.21			
San Mateo	0.23	0.77	Charlotte	0.36	-0.63	Orange	0.36	0.05			

Top 10 Status Quo Bias Counties

California			**Florida**			**New York**			**Vriginia / DC**		
County	SQB	Ln Pop Density	County	SQB	Ln Pop Density	County	SQB	Ln Pop Density	County	SQB	Ln Pop Density
San Bernardino	0.76	-1.20	Manatee	0.82	-0.01	Rockland	0.43	1.16	Loudoun	0.10	0.48
Orange	0.81	1.78	St. Lucie	0.93	0.04	Queens	0.45	2.94	Henrico	0.44	0.98
Santa Cruz	0.87	0.05	Sarasota	0.94	0.25	Richmond	0.47	2.06	Chesapeake city	0.44	0.40
Shasta	0.90	-1.91	Citrus	0.97	-0.72	Saratoga	0.65	-0.39	Chesterfield	0.59	0.52
Napa	0.90	-0.75	Seminole	1.10	0.98	Rensselaer	0.70	-0.50			
Riverside	0.93	-0.23	Martin	1.17	-0.61	Suffolk	0.71	0.33			
Fresno	1.12	-0.83	Clay	1.18	-0.24	Erie	0.77	0.49			
Stanislaus	1.21	-0.15	Pasco	1.20	0.28	Nassau	0.77	1.68			
Ventura	1.49	-0.09	Marion	1.31	-0.61	Schenectady	1.66	0.48			
Tulare	1.58	-1.29	Indian River	1.41	-0.48	St. Lawrence	2.13	-2.07			

Notes. 1. This table lists the top 10 and bottom 10 counties ranked based on estimated status quo bias in California, Florida, New York and DC/Virginia. 2. Status quo bias estimates are calculated based on the outflow gravity regression in column 1 of Table 1 using historical search friction controls only.

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Appendix A

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

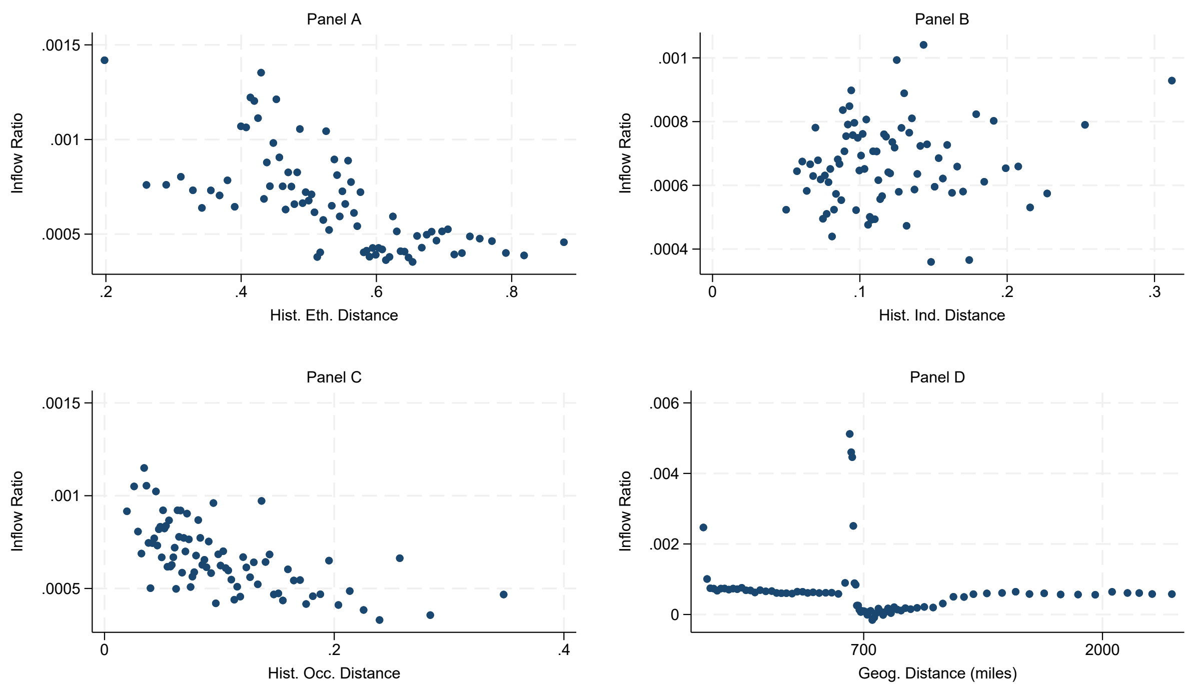
$$M_{mn} = \frac{\alpha_{mn}}{O_m I_n} \frac{L_n \times [N_m(1-u_m)]}{\sum_i N_i(1-u_i)}$$

as displayed in (11) and

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

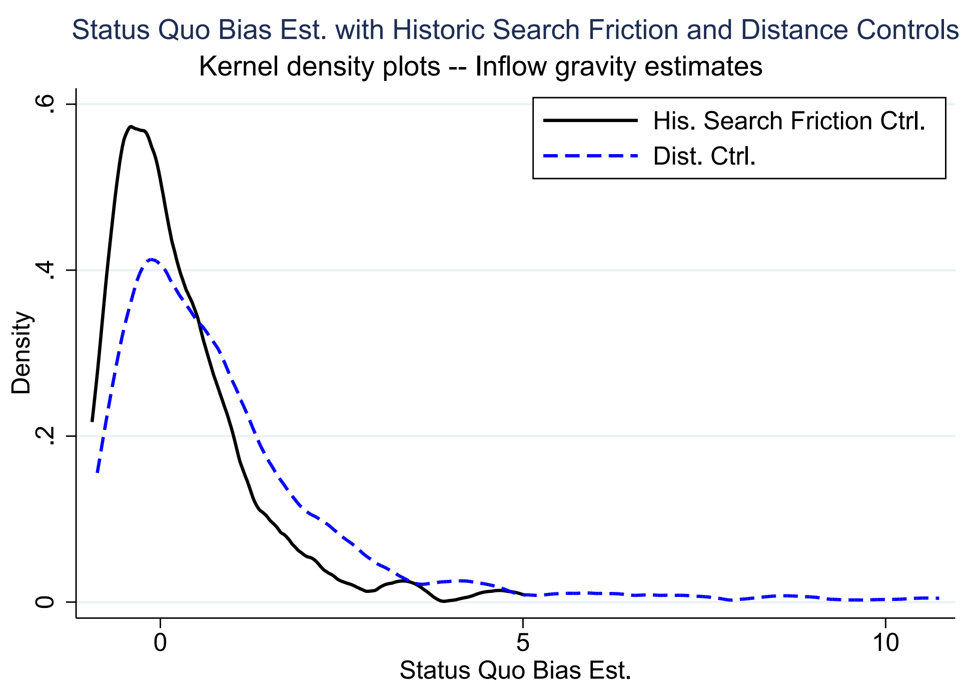
as displayed in (13). As discussed, total migration between two locations depends on (i) bilateral status quo bias adjusted search intensity α_{mn} normalized by both outward and inward multilateral resistance O_m and I_n, (ii) a population product, involving the total number of employed workers native 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 $\sum_i N_i(1-u_i)$.

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



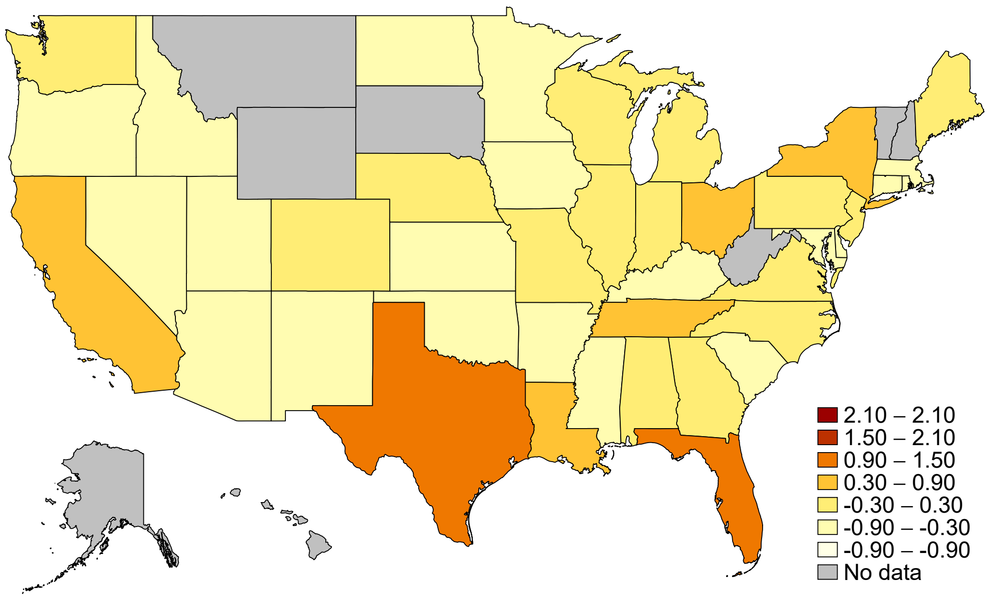
Notes. 1. This figure presents a binscatter plots of the relationship between U.S. county level population inflow ratio (bilateral population outflow / total non-movers at source, 2014-2018 average, ACS) and search intensity controls. 2. Historic ethnic distance is constructed according to equation (21) 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 historic occupation composition difference is similarly constructed according to equation (21) using historical (1940) industry and occupation composition shares. 4. Geographic distance is the distance between county pairs.

Figure A2: County-Level Status Quo Bias (b_n) Dispersion (Inflow Gravity).

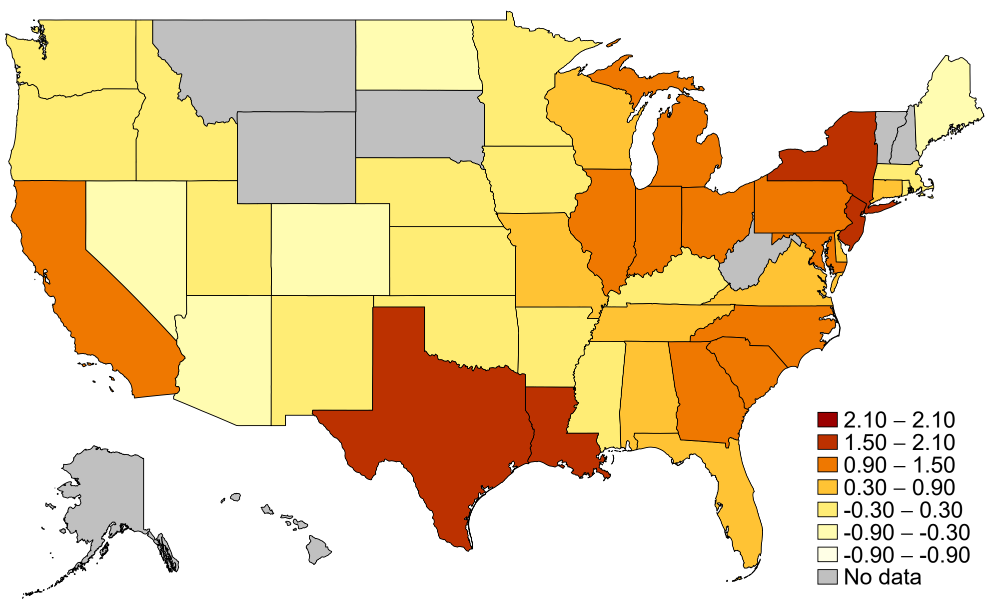


Note: This figure displays kernel density estimates of status quo bias b_n based on OLS inflow gravity regressions in columns (4) and (5) of Table 1 with robust standard errors clustered at the origin and destination county levels.

Figure A3: The Geography of Average State-Level Status Quo Bias (Inflow Gravity)



(a) Panel A. State-Level Status Quo Bias Using Historical Search Friction Controls

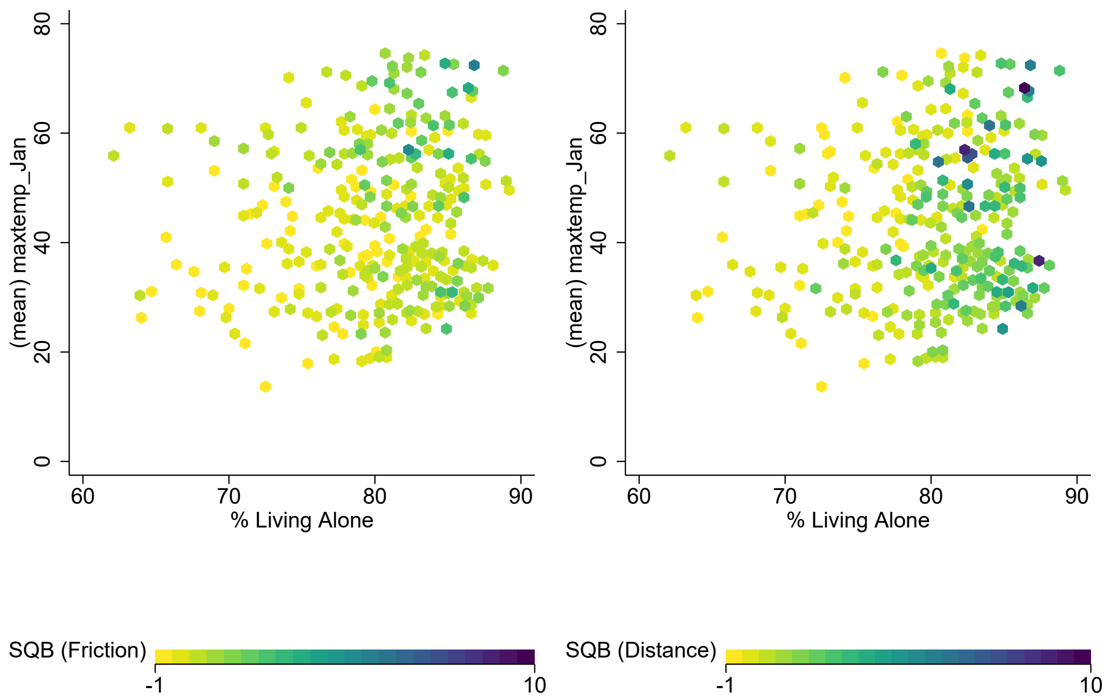


(b) Panel B. State-Level Status Quo Bias Using Geographic Distance Control

Notes. 1. Figure A3a displays state-level average status quo bias (b_n) estimated based on OLS inflow gravity regressions in columns (1) of Table 1. 2. Figure A3b displays state-level average status quo bias (b_n) estimated based on OLS inflow gravity regressions in columns (1) of Table 1.

Figure A4: The Correlates of Status Quo Bias Estimates (Inflow Gravity)

(a) Status quo bias, Environmental Considerations and Family Support



(b) Status quo bias, Community-Level Political Orientation and Religiosity

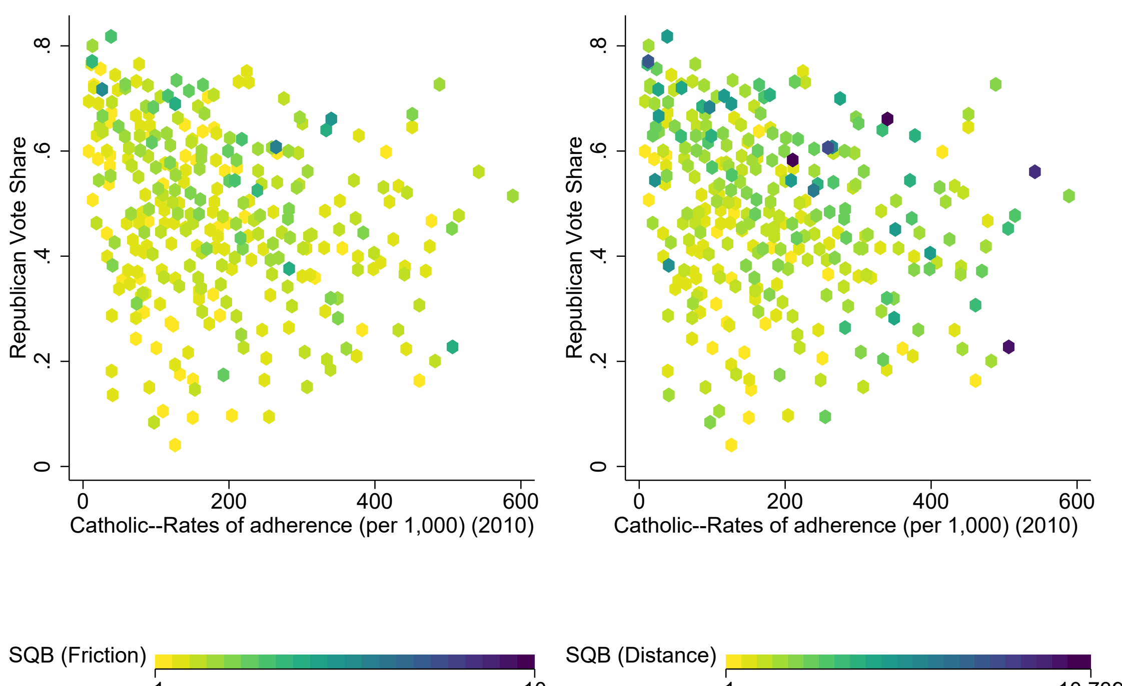
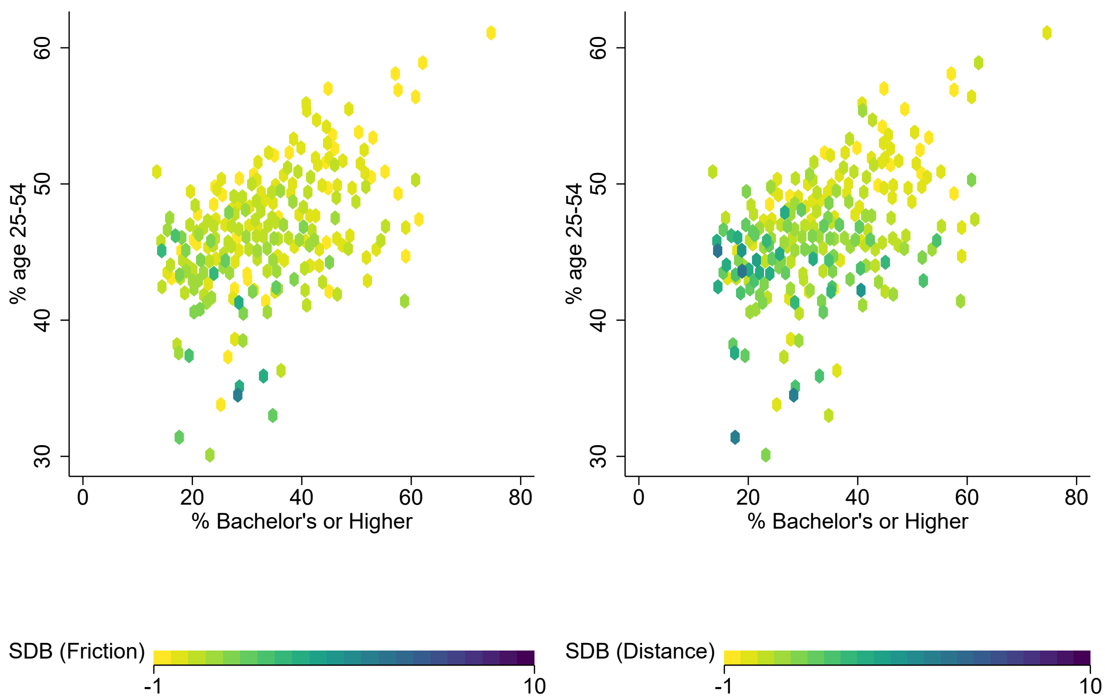


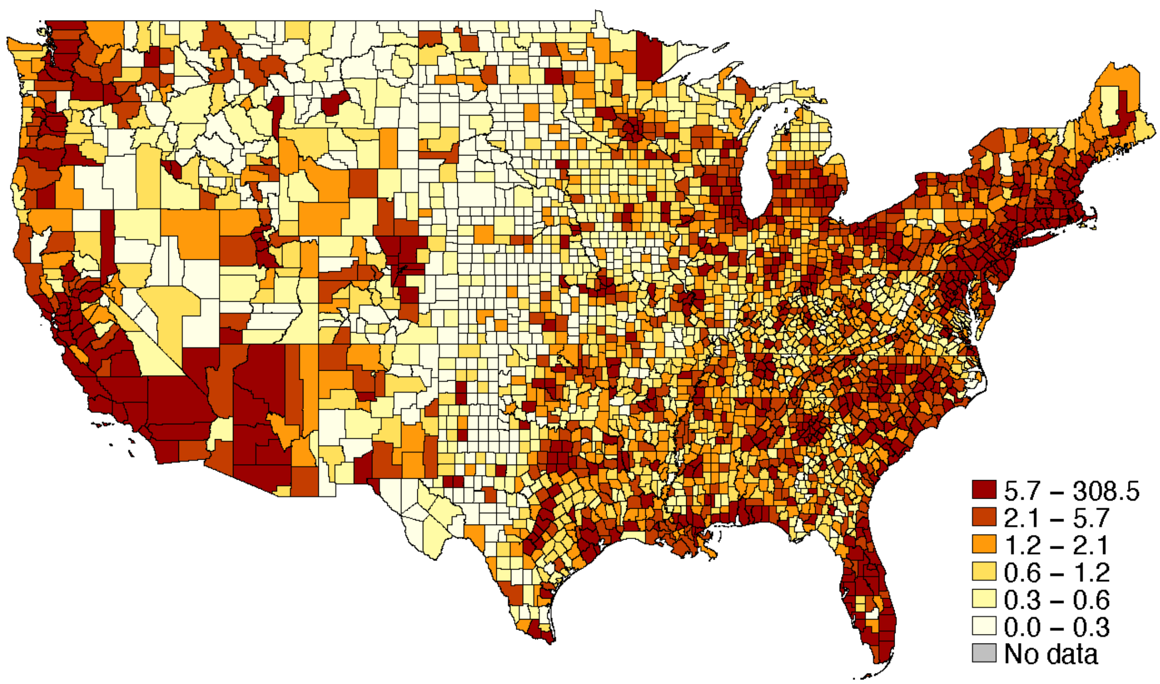
Figure A4: The Correlates of Status Quo Bias Estimates (continued)

(c) Status quo bias, Working Age and College Educated Population



Notes. 1. This figure presents heat plot visualizations of the raw data relationships between status quo bias estimates and three sets of correlates. 2. SQB (Friction) denotes status quo bias estimates based on the inflow gravity regression in column 1 of Table 1 using historical search friction controls only. 3. SQB (Distance) denotes status quo bias estimates based on the inflow gravity regression in column 2 of Table 1 using geographical distance. 4. Shades of color indicate levels of estimated status quo bias in the corresponding cells. 5. Figure A4a plots the relationship between maximum mean temperature in January and county-level share of population living alone. 6. Figure A4b plots the relationship between county-level Repubican vote share and the rate of adherence to Catholicism (per 1000 population) in 2010. 5. Figure A4c plots the relationship between county-level share of working age population (between 20-54) and the share of population with a Bachelor's degree or above.

Figure A5: Geographic Distribution of Social Connectedness



Notes. 1. This figure displays state-level average social connectedness using the Facebook Social Connectedess Index in Equation 24.

Table A1: List of Variables in Lasso Regressions.

Variable Group	Variable List
Commute	log avg. commute time, % commuters, % drive alone, % carpool, % take public transport
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
Environment	heat days, July precipitation, January maximum temperature, and July max temperature
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
Marriage	% living alone, % with children, % divorced, % grand parents caring for children
Public assistance	% household on social security, % household with retirement income, % household with supplemental security income, % household with public assistance, % household with food stamp, and % percent household below poverty line
Religious	% Evangelical, % Catholic, and % Mainline Protestant
Social Capital	crime per capita, and republican vote share

Table A2: Predictors of Status Quo Bias (Inflow Gravity Estimates)

Status Quo Bias Estimates (His. Search Friction Controls)	Coefficients (Inflow Gravity)	Status Quo Bias Estimates (Geographical Distance)	Coefficients (Inflow Gravity)
Maximum January temperature	0.197	% living alone	0.175
% aged between 20 and 54	-0.170	% divorced	-0.163
% housing built between 1990 and 1999	-0.108	% aged between 20 and 54	-0.144
% drive alone	0.086	Republican Vote Share	0.141
% housing built between 1950 and 1959	0.078	% housing built 2010 or later	-0.124
% living alone	0.064	Log avg. commute time	0.103
% commuters	-0.059	% with children	0.084
% with children	0.044	Log population density	-0.084
% Black	-0.041	% males	-0.077
% Hispanic	0.040	% housing built between 1980 and 1989	-0.064
Republican Vote Share	0.040	% Bachelors or more	-0.053
Log avg. commute time	0.039	Heat days	0.051
Log population density	0.037	% foreign born	-0.039
July precipitation	-0.030	% housing built between 1940 and 1949	0.033
% Grandparents caring for children	-0.018	% housing built between 1970 and 1979	-0.022

Note: This table lists the top 15 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 A1