Internal Migration and the Microfoundations of Gravity*

Greg Howard† Hansen Shao‡

March 5, 2022

Abstract

We propose a model that can match gravity patterns of U.S. interstate migration based on persistent and spatially-correlated preferences. The model also matches many untargeted dynamic moments of migration, previously a challenge for the literature. From the model, we learn five lessons with implications for regional evolutions, migratory insurance, and macroeconomic misallocation: moving costs need not be large to generate gravity patterns; return migration patterns can be the result of persistent preferences; short-run elasticities of migration vary by distance; bilateral migration flows are informative of population elasticities to local shocks; and short- and long-run population elasticities are the same.

Keywords: regional evolutions, migratory insurance, misallocation, gravity equation, labor mobility

JEL Codes: R23, R13, J61

*We would like to thank the Illinois Macro Lunch and Illinois Young Applied Faculty Lunch for constructive feedback.

†University of Illinois, glhoward@illinois.edu.

‡University of Illinois

Internal migration is central to how regions evolve, acts as a key insurance mechanism against regional economic shocks, and leads to macroeconomic misallocation when there are barriers to moving. For these reasons, internal migration is a key element of a growing literature on dynamic spatial general equilibrium models. The primary empirical feature of internal migration is its gravity relationship: migration between two locations increases with the population of each location and decreases with distance. In this paper, we argue that this gravity relationship is the outcome of persistent and spatially correlated preferences, and we show that modeling migration this way has important lessons for regional evolutions, insurance, and misallocation.

We propose a model in which personal preferences over location are persistent and spatially-correlated. The model is simple but distinct from the existing migration literature. We demonstrate that our assumption generates a gravity relationship. We calibrate the model's two parameters, one governing the persistence and one the spatial correlation, in order to match the gross migration rate and the relationship between migration and distance in the United States.

The model is also successful at matching untargeted dynamic moments of migration, something that has been a challenge for the literature. We show in the model that the migration rate over t years, i.e. the number of people living in a different state than they did t years ago, should be close to proportional to the square root of t. When we look at the data, the square root is a good approximation in the Gies Consumer Credit Panel data for up to 14 years, the length of the panel. We also look at other moments: the model is able to match the distribution of the number of times a person moves over many years and the conditional probability of migration given a previous move.

With our model in hand, we show five lessons focusing on the potential for misallocation, regional evolutions, and insurance.

The first lesson we find is that moving costs are not essential to generate real-world gravity patterns. The literature has typically estimated large moving costs as the source of the gravity relationship. For example, Kennan and Walker (2011) estimates costs that average several hundred thousand dollars. These moving costs imply that there is enormous misallocation between where people are and where they would like to be. However, our model—which does not feature moving costs—shows that there are other ways to rationalize the observed migration patterns. Compared to existing models, ours suggests there is less opportunity for policy to lower migration costs in the hopes of reducing missallocation.

The second lesson is that the dynamics of migration can be a natural consequence of persistent preferences. The high rate of return-migration, in which people leave and then come back, has been a focus of the literature, and information revelation about a new location has been the typical solution to match the dynamics (Kennan and Walker, 2011; Kaplan and Schulhofer-Wohl, 2017). Here, we show this is not necessary to match the data, and therefore, the fact that there are high rates of return migration is not sufficient to prove those forces are quantitatively important.

The final three lessons are directly about regional evolutions, with consequences for the insurance that comes from migration, as well as any local policy that affects the attractiveness of an area.

The third lesson is that short-run cross-elasticities of migration to utility vary by distance, with closer locations being more elastic. For example, migration between Louisiana and Mississippi is more elastic to utility changes in Louisiana than migration between Louisiana and New York. We check this prediction in the data using the Hurricane Katrina shock.

The fourth lesson is that bilateral migration flows are helpful to calculate population elasticities. The amount of migration is related to the mass of people who are roughly indifferent between living in two locations. In fact, the population elasticity is linearly proportional to the current migration, adjusted for the spatial correlation of the personal utility shocks. This lesson has important implications for thinking about counterfactuals and welfare. Because high-gross-migration regions are more population elastic to local changes, the welfare benefits of a policy helping workers in a high-gross-migration region will be larger than the same policy in a low-gross-migration region, all else equal. Also, the population displacement happens close to the affected states, so the welfare benefits accrue to people that were originally in nearby states. Finally, spatially-correlated shocks will cause less population adjustment than spatially-uncorrelated shocks.

The fifth and final lesson is that short-run and long-run population elasticities are the same. In other words, the implications of the fourth lesson hold in both the short- and long-run.[1] This has implications for how much persistence in population and migration dynamics that we should expect. For example, in dynamic logit models, which are the most common model in the literature, migration flows are very persistent. In that model, if a state's utility increases permanently, people who get an idiosynchratically high utility draw will move there, year-after-year. So the state will have a persistent increase in net migration. In our persistent correlated preferences model, the population adjustment occurs immediately, as the people who were close to indifferent move, but the next period, there is no continued population adjustment. In fact, the counterfactual population movements of any spatial policy or shock will look very different.

We illustrate the importance of these final two lessons by discussing the consequences of the Rust Belt decline over 1980 to 2018. One of the key features of the decline was that it was spatially correlated, and so migration provides less insurance than it otherwise would. We show this quantitatively by considering a counterfactual, where the utility of Pennsylvania declines in a way consistent with the data, but other states evolve according to the national average. In both scenarios, migration provides insurance against the negative shock because people will move to less affected states. But in the data, the states to which they are most likely to move are also experiencing similar declines, and so the insurance from migration is reduced by 25 percent.

[1]This is not true in a dynamic logit model. In those models, the data about migration determines the short-run elasticities, but the long-run elasticities do not depend on the migration matrix.

Literature

There has long been an interest in understanding economic activity in space, with key contributions from Rosen (1979), Roback (1982), Krugman (1991), and Blanchard and Katz (1992), among many others.

In recent years, the dynamic spatial literature has grown quickly, with a big emphasis on migratory patterns.[2] One of the first papers in this literature was Kennan and Walker (2011), which modeled migration using a rich dynamic logit model and was able to capture many important features. They especially focus on including features in the model that allow them to match dynamic moments of migration, such as a large amount of return migration.

In recent years, the literature has built on this model to analyze economic trends and important empirical phenomena. Kaplan and Schulhofer-Wohl (2017) analyze why rates of gross migration have declined, finding key roles for information and increasingly similar opportunities across space. Caliendo, Dvorkin and Parro (2019) analyzes the effects of the China shock in dynamic spatial general equilibrium. Amior and Manning (2018) analyzes the race between migration and job loss, to see why local joblessness is so persistent. Liu, Klieman and Redding (2021) analyzes the speed of adjustment to regional shocks. Allen and Donaldson (2020) looks at dynamics over generations and argues that path-dependence is a major feature of the spatial economy. Giannone (2017) analyzes the end of regional convergence, attributing it largely to skill-biased technical change. Eckert and Peters (2018) studies the way structural change impacts the agricultural share. Schubert (2021) analyzes the spatial dynamics of housing markets, emphasizing spillovers that come through migration. Mangum and Coate (2019) augments the models with a preference for living near a home location, and shows how that could play a role in declining migration rates. Mon-

[2]There is also a large literature on the microfoundations of the gravity equation for trade. See, for example, Bergstrand (1985), Helpman, Melitz and Rubinstein (2008), and Chaney (2018). There are several reasons that the microfoundations of gravity for migration and for goods might be different. At the most basic level, the decision-makers for migration are what is being measured, whereas decision-makers for trade are importing or exporting, and it is the goods being measured. Migration also has a dynamic element to it, as people make repeated decisions on where to live.

ras (2018) analyzes the asymmetry of the responsiveness of inmigration and outmigration. Porcher (2020) considers the role of information frictions in shaping migration decisions. Tombe and Zhu (2019) study the changes in trade and migration costs within China, and Hao, Sun, Tombe and Zhu (2020) study the role of migration policy in China on growth and structural change. Bryan and Morten (2019) look at the effects of migration barriers on aggregate output in Indonesia. Oliveira and Pereda (2020) look at the impact of climate change on internal migration in Brazil.

Despite the diversity of interesting topics, all of these papers are linked because migration is a central part of the theoretical framework, and all of them use a dynamic logit formulation which is dominant because it generates realistic gravity patterns and is particularly tractable. In fact, Caliendo et al. (2019) uses it to derive a dynamic exact-hat methodology of solving for counterfactuals, and Liu et al. (2021) shows that it can be linearized. Our paper makes a methodological contribution, by digging into why the gravity relationship exists and showing what we can learn from it. To do that, we depart from the dynamic logit formulation, sacrificing some of its tractability, but gaining the ability to match realistic dynamics and do a better job evaluating welfare and counterfactuals.

1 Persistent correlated preferences

1.1 Model

This section includes a model that generates a gravity relationship, based on persistent correlated preferences. Notationwise, n denotes the individual, i the location, and t the year. Individuals pick their location to maximize utility:[3]

$$u_{nt} = \max_i u_{nit} = \max_i u_{it} + \epsilon_{nit} \tag{1}$$

To denote it using vectors of size $I \times 1$,

$$u_{nt} = \max \vec{u}_{nt} = \max \vec{u}_t + \vec{\epsilon}_{nt} \tag{2}$$

where

$$\vec{\epsilon}_{nt} = \rho \vec{\epsilon}_{n,t-1} + \sqrt{1-\rho^2}\vec{\eta}_{nt} \qquad \text{and} \qquad \vec{\eta}_{nt} \sim N(0, \Sigma) \tag{3}$$

Note that ϵ_{nt} also has variance Σ.

We assume that states that are closer to one another have a higher correlation of personal utility by using the following functional form:

$$\Sigma_{ij} = \exp(-a \text{ distance}_{ij}) \tag{4}$$

where a is a parameter and distance_{ij} is the distance between i and j.

Proposition 1. Σ *is positive-definite.*

Proposition 1 establishes that creating a covariance matrix based on a completely monotone function of distance is always going to create a positive definite matrix, so it can be applied to other countries or geographic divisions of the United States. Proofs are collected in Appendix A, but the key to the proof is to show that $exp(-ax)$ is completely monotone and then to apply the Schoenberg Interpolation Theorem (Schoenberg, 1938).[4]

[3]Equation (1) assumes that agents are myopic. This is more restrictive than necessary, as the agents can costlessly move every period. In other words, the agent's location is not a state variable. However, it is restrictive as it rules out the possibility of accumulating capital, either through savings or acquiring skills. This is a common assumption in the literature (Caliendo et al., 2019; Liu et al., 2021), as keeping track of wealth distributions across many locations is computationally infeasible. In sum, the model needs to impose that agents cannot save or invest, but the fact that agents are myopic is easily relaxed without changing any implications.

[4]The restriction that the function is completely monotone is restrictive. However, there are other func-

Migration occurs when the location j that maximizes utility u in time t and time $t-1$ are different.

Why does having a high correlation for idiosynchratic shocks increase the migration between two regions relative to other regions? The effect is subtle. It is not because the two regions have more people who prefer one in the past period and now prefer the other. For example, if there are only two regions with equal baseline utility, then the correlation does not matter: a fraction independent of the correlation will migrate between the two regions each period. With more regions, it is still true that the fraction for which i becomes more preferable to j is a constant fraction for any i and j regardless of the correlation. But in this case, the number of movers is also dependent on having a high value for both i and j, which is more likely to occur when i and j are highly correlated. As a concrete example, consider two locations with a joint normal distribution where the mean utility is zero and the variance is 1 for both locations, with correlation Σ_{ij}. Regardless of Σ_{ij}, the number of people for which $\epsilon_{it} > \epsilon_{jt}$ and $\epsilon_{it+1} < \epsilon_{jt+1}$ is determined only by ρ, the persistence of the preferences. However, the distribution of the values of ϵ_{it} for which switchers, who prefers i to j in period t, but prefers j to i in period $t+1$, as $\rho \to 1$ is distributed $N(0, \frac{1}{2} + \frac{1}{2}\Sigma_{ij})$. If Σ_{ij} is not large, then there are very few switchers in the far right-tail, meaning they probably did not live in i or j to begin with, and therefore do not migrate from i to j.[5]

1.2 Data

We use two main sources of data for the project, IRS migration data and the Gies Consumer and Small Business Credit Panel (IRS Migration Data, 2004-2018; Experian, 2004-2018).

tions besides $\exp(-ax)$ that would work, such as $1/(1+ax)$.

A caveat to this exercise is that the Schoenberg Interpolation Theorem applies to distances in $\mathbb{R}^n$ but not necessarily to distances on a sphere. However, the correlation between distances measured using Vincenty (1975)—which we use in this paper—and distances calculated using the Pythagorean Theorem based on longitude and latitude is 0.98. In practice, we do not encounter any non-invertible matrices regardless of how we parametrize a.

[5]Having a more correlated shock also reduces the population of the two locations. For example, if the correlation is close to 1, the two locations only get one effective draw to live in the two locations, whereas if they are uncorrelated, there are two chances to pick one of the locations. This also increases the migration rate, once it is normalized by population.

The IRS data has aggregated data on state-to-state migration, useful for estimating a gravity equation, while the credit data is a 15-year panel of individuals making up a 1 percent sample of the United States. It records the state of residence. The two datasets have similar gross migration rates, which can be seen in Figure 1.[6] One reason the credit data may have a higher migration rate is that not everyone has a credit report. In particular, lower income people tend to not have credit reports, and are also less likely to move. The two datasets also exhibit similar gravity patterns, which we show later in Table 2.

While there are some well-known drawbacks to the IRS data, e.g. it is based only on tax filers, it is one of the most comprehensive administrative datasets keeping track of migration.[7]

Similarly, while credit data is not designed as a dataset to study migration, it does have location information, and the bureau gets the addresses from a person's financial accounts. The biggest concern with credit data is that moves may show up with a lag, as people do not always immediately change their addresses with their financial institutions. The Gies credit data is an unbalanced panel, with yearly observations occurring in May. For matching migration patterns and rates, we focus on the 2004-2005 period, so we only observe data if they had a credit report in both of those years. For some of the dynamics, we address the unbalanced nature of the panel depending on the moments of the data that we are interested in.

To calculate distances between states, we use the geographic center of each state from Rogerson (2015) and calculate distances using the formula from Vincenty (1975).

1.3 Parametrization

We parametrize ρ, a, and u_i in order to match the probability of migration, the coefficient on distance in a gravity equation, and the population in each region. For the gravity moment, we

[6] For comparison, we also show the migration rates in the American Community Survey, which are lower, but on the same scale.

[7] It is not well understood why the migration rate is so low in 2014 or so high in 2016, as these anomolous values did not show up in other datasets measuring migration. See DeWaard, Hauer, Fussell, Curtis, Whitaker, McConnell, Price and Egan-Robertson (2020).

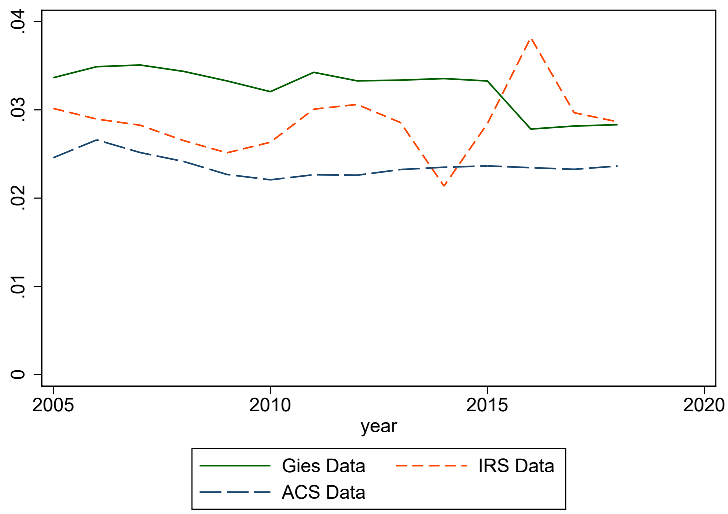


Figure 1: Comparison of interstate migration rates in IRS, ACS, and Gies data

Table 1: Parameterization

Parameter	(1) Value	Moment	(2) Data	(3) Model
a	0.000299	Distance coefficient	-0.7376	-0.7376
ρ	0.999627	Average migration	0.0334	0.0334
u_i		Population of each state		

run a Poisson regression of migration on log population of the origin state, log population of the destination state, and log distance. We match the coefficient on log distance. We simulate ten million workers for two periods.[8]

ρ, which represents how persistent people's tastes shocks are, is helpful to match the average amount of migration. The best match involves a very persistent taste shock of more that 0.999. a, which is about how correlated tastes are across space, is used to match the gravity coefficient. Here, distance is measured in kilometers, so a is not particularly interpretable, but the value is .000299 meaning that correlation of shocks for two states 1000 kilometers apart is about 0.74. The u_j are picked to match the population of each state. Unlike a logit-model of location choice, there is a less than perfect correlation between log

[8]Even though there are ten million individuals in the simulation, the outcomes are discrete, and so the typical techniques based on differentiation are not helpful to do the simulated method of moments. See Appendix B for details.

population and u_j. In this parametrization, it is 0.64.

1.4 Gravity-related moments

To test the calibrated model, we run some gravity regressions using different datasets. It is known that running a gravity regression can deliver different coefficients depending on the exact nature of the regression equation. We first run a typical Poisson regression (Silva and Tenreyro, 2006; Correia, Guimaraes and Zylkin, 2019):

$$\log m_{i\to j} = \alpha \log p_i + \gamma \log p_j - \beta \log \text{distance}_{ij} + \epsilon_{ij} \tag{5}$$

where p_i is the population of i and $m_{i\to j}$ is the migration from i to j.

Table 2 shows the results using IRS data (Column 1), Credit data (Columns 2 and 4), and simulated data from the calibrated model (Column 3 and 5). The first three columns are the estimated coefficients from the typical Poisson regression, specification (5). Since we target the coefficient on distance in a gravity equation, the estimated coefficients are similar by construction. The coefficient from simulated data is not significantly different from the results from IRS data. Also, the coefficients on origin population and destination population are very similar across three different datasets even though we are not targeting these coefficients.[9]

The last two columns in Table 2 use a different specification. We replace the population terms with state-level fixed effects. Again, the estimated coefficients are comparable.

We also compare the relationship of distance and migration non-linearly. Figure 2 shows a binscatter plot of migration adjusted for populations and distance. First, we divide the number of migrants by the product of origin and destination population, for both the IRS

[9]One possible reason for the coefficients on population being less than one is that we model the personal preferences as normal. Normal distributions have an increasing hazard function, so the probability of being near a cutoff, conditional on being above that cutoff, increases as the cutoff gets bigger. In this context, people who live in low-utility states—and therefore must have very high draws of personal utility for that state—are more likely to be close to indifferent with another state.

Table 2: Gravity Equations

	(1) Migration (IRS)	(2) Migration (Credit)	(3) Simulated Migration	(4) Migration (Credit)	(5) Simulated Migration
Log Distance	-0.736***	-0.744***	-0.744***	-1.063***	-0.978***
	(0.0572)	(0.0515)	(0.0396)	(0.0672)	(0.0552)
Log Origin Population	0.900***	0.923***	0.892***		
	(0.0832)	(0.0797)	(0.0486)		
Log Destination Population	0.822***	0.893***	0.889***		
	(0.0976)	(0.0799)	(0.0501)		
Observations	2550	2550	2550	2550	2550
R^2					
Pseudo R^2	0.725	0.719	0.903	0.847	0.949
Origin and Destination FEs				Yes	Yes

Standard Errors are two-way clustered by origin and destination states

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

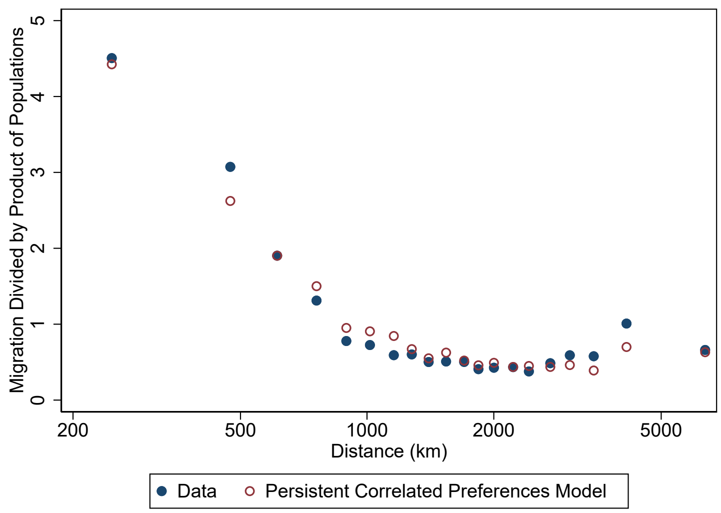


Figure 2: Migration and distance

data and the simulation. Since the units are not particularly interpretable, we normalize this measure to have mean 1. Then we separate the state-pairs into bins based on the distance between states and plot the mean within each bin. Even though our parametrization did not target this pattern, the simulated data and the IRS data look similar. In the bin with the closest states, population-adjusted migration is about five times higher than average for both the data and the simulation. For distance bins over 2000 kilometers, migration is about half of the average.

1.5 Extensions

This persistent correlated preferences model was developed as a starting point to explain the gravity relationship in migration data. But it is flexible enough to easily extend it to allow for heterogeneity and other important moving patterns.

One of the first-order things about migration is that it is highly heterogenous along demographic lines. Young people and college-educated people move at higher rates than other people (Molloy, Smith and Wozniak, 2011). Having a demographic-dependent ρ_d would be able to match different migration rates without changing the rest of the economics. In fact, because migration is almost directly proportional to $\sqrt{1-\rho^2}$ when ρ is close to 1, it is fairly straightforward to calculate the appropriate ρ_d's for different demographics, and the model would still approximately aggregate to $\sqrt{1-\rho_{\text{agg}}^2} = \sum_d \frac{L_d}{L}\sqrt{1-\rho_d^2}$, where L_d/L is the fraction of the population of demographic d.[10]

Another relatively simple way to extend the model is to consider other similarities besides distance that could drive migration. For example, there is more migration between states with similar levels of education. While the proof of Proposition 1 does impose requirements on the functional form, including that distance_{ij} be a norm in $\mathbb{R}^n$, we can include other measures in our definition of distance that allow us to match other deteminants of migration. For example, we could imagine a distance in $\mathbb{R}^3$, where the three dimensions are latitude, longitude, and education levels. We carry out this exercise in Appendix C.

2 Dynamic moments

Matching the dynamic moments has long been a challenge for migration models. For example, in the data, more than 20 percent of migrants move back to their origin location the next year. This is one of the features of migration that Kennan and Walker (2011) put great

[10] A model with this type of heterogeneity would have slightly different implications for the dynamic moments of migration that are discussed in the next section. However, some of the key moments, such as Proposition 2 would still be the same.

effort into matching because it is not a natural consequence of the dynamic logit.[11] In this section, we show that persistent correlated preferences provides a natural rationale for the dynamic patterns we observe in the data.

2.1 Migration rates at different horizons

We start by looking at the the moving probability at different horizons. Define the t-year migration rate to be the probability of living in a different location than the location t years ago. We show this dynamic moment first because we can show an important proposition. The other moments we consider will be based only on simulation.

Proposition 2. *Holding the u_i's constant over time, as $\rho \to 1$, the t-year migration rate is proportional to $\sqrt{t}$, i.e.*

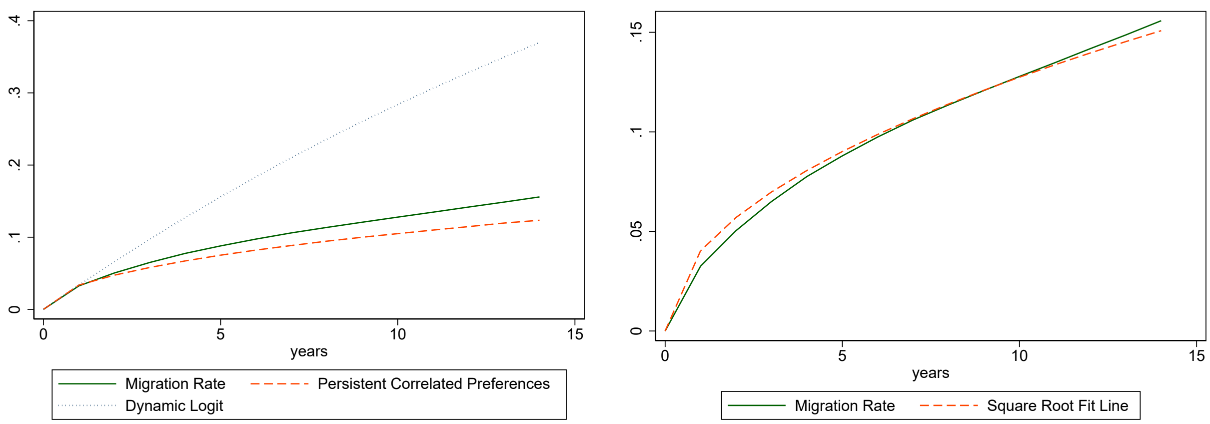
$$m_{i \to j,t} = m_{i \to j,1} \sqrt{t} \tag{6}$$

where $m_{i \to j,t}$ is the t-year migration rate.

In Figure 3, we show the t year migration rate does follow a square root pattern in both the data and in a simulation of persistent correlated preferences. For the data, we include any observations for which we have credit reports t years apart, so it should be noted that the sample changes slightly depending on t.

The model and the data do not provide a perfect match, with the model predicting smaller migration rates at long horizons than the data. This is likely due to the fact that when we parametrize the model based only on one year of data, to which the long-run migration rates are very sensitive. For example, any measurement error in the one-year migration rate is going to be amplified by approximately $\sqrt{14}$ in the simulated 14-year migration rate. Nonetheless, the shape of the data is very close to a square root, which we show in Figure 3b. Here, we simply pick the best constant c such that $c\sqrt{t}$ minimizes the sum of squared residuals with the data.

[11] They solve this problem by assuming that people learn something (e.g. their wage) about the location they move to once they arrive, and if it is not to their liking, they move back or continue their search.



(a) Migration rate in the data and models

(b) The fit of a square root

Figure 3: Migration Rates at Different Horizons. Migration rate is calculated as the percentage of people living in a different state than they did t years ago.

In contrast, in a dynamic logit model where the autocorrelation of migration is close to zero, the t-year migration rate is much more linear.[12]

2.2 Number of moves

Of course, the t-year migration rate is not the typical way the dynamic moments of migration are presented in the data, so it is important that the model is able to capture the more-common moments as well. A natural moment is the distribution of the number of interstate moves over time.

Figure 4 looks at how many moves are made over a 14 year period. In the data, a large majority of people make zero moves, but some people make many moves. Here, we include in this chart only people for whom we have data in all 15 years (for up to 14 possible moves).

However, if moving is a Markov process, as predicted by a simple logit model, many fewer people would make zero moves, many more people would be making one move, and fewer would be making a large number of moves compared to the data. In our persistent

[12]The dynamic logit line is based on a dynamic logit model in which bilateral moving costs are picked to match migration flows exactly, and the u_i's are chosen to match population. Details of this model are in Appendix E. The autocorrelation is not quite zero because the migration rate in nearby locations are correlated.

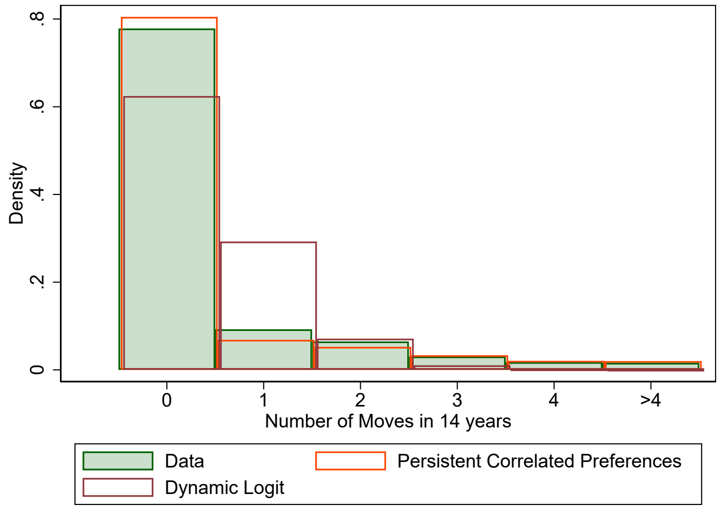


Figure 4: Number of moves in 14 years. Number of individuals: 1,796,913

correlated preference model, someone who moved last year is still fairly indifferent between the two locations, so they are likely to move again. Because of this persistent preference, this model matches the distribution of the number of moves much better, especially the share of people making two or more moves.

2.3 Return and onward migration

Another common moment is to look at the conditional probability of moving given a previous move. This is sometimes split up between onward and return migration. Return migrants are those who move back to their original state after an interstate move. Onward migrants move to a new state after an interstate move, and the new state is not the state where they came from.

Figure 5 shows the probability of return migration and onward migration in different time horizons after an interstate move. In the credit data, around 21 percent of migrants move back to their origin state one year after their initial move, and another 5.6 percent move to a new state. For migrants who stay at the destination state for four years, 3.4 percent move back to the original state in the fifth year and 3.3 percent move to a new state in the fifth

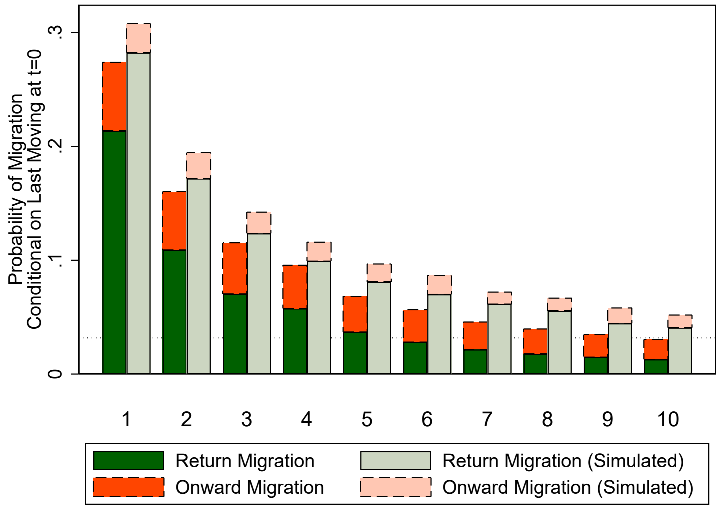


Figure 5: Return and onward migration

year. To be included in this analysis, a person must show up for the number of years that would be necessary to calculate the statistic, but we do not use a balanced panel.

Since we do not target these statistics in the calibration, the simulated statistics do not match the data perfectly. In the simulated data, around 28.2 percent of migrants move back to the origin state one year after the inter-state migration, and 2.1 percent move to a new state. The return migration rate is generally higher in the simulated data, and the onward rate is lower. But the simulated data capture the trend. The reason is again quite simple. Conditional on having moved recently, the agents are likely relatively indifferent between the two regions, and are likely to move back. The longer they have stayed in one region, the more likely that their accumulated preference shocks have drawn them further away from being indifferent, so the probability of return migration decreases over time.

3 Lessons for spatial economic models

We think there are five important lessons that can be learned from the persistent correlated preferences model.

3.1 Gravity can arise from persistent correlated preferences

The first lesson is a proof-of-concept: a model with persistent correlated preferences can generate gravity patterns, and it can do so without moving costs. The literature has long proposed large moving costs to keep people from moving, magnitudes larger than observed costs for a physical move. For example, Kennan and Walker (2011) estimates moving costs in excess of 300,000 U.S. dollars (in 2010) on average. This model proves that moving costs are not a necessary ingredient to match a realistic relationship between migration and distance. Therefore gravity patterns themselves are not evidence that moving costs are large.

3.2 Migration dynamics can arise from persistent correlated preferences

The second lesson is similarly proof-of-concept: a model with persistent correlated preferences can match the dynamics of migration. As in the first lesson, the literature often presumes that the dynamics are a result of learning or dynamic moving costs. In the learning story, people show up to a new place, discover they do not like it, and return (e.g. Kennan and Walker, 2011; Kaplan and Schulhofer-Wohl, 2017). In the dynamic moving costs models, moving costs are lower in the first few years subsequent to a move. In contrast, the persistent correlated preferences model is able to match the dynamics of the migration, despite having only been calibrated to match the static gravity moments. Of course, this does not prove that learning or dynamic moving costs are not real. Rather, it shows that they are not necessary, and therefore that the dynamics of migration do not prove they are quantitatively important.

3.3 Migration elasticities decrease in distance

The third lesson is important for thinking about policies and counterfactuals, and concerns the short-term migration elasticities to changes in local utility.

Proposition 3. *Holding the u_i's constant over time, as $\rho \to 1$, the short-run local semi-elasticity of migration from i to j to utility in i is*

$$\frac{\partial \log m_{i\to j}}{\partial u_i} = \kappa \cdot \frac{1}{\sqrt{1-\Sigma_{ij}}} \tag{7}$$

for some constant κ that does not depend on i or j. Recall that Σ_{ij} is the covariance of idiosyncratic utility for states i and j.

Recall, that $\Sigma_{ij} = \exp(-a \text{ distance}_{ij})$. So the magnitude of elasticity is decreasing in distance. The difference in elasticities is sizable but not enormous. A pair of states 220 kilometers apart (roughly the first percentile) have an elasticity that is 4 times greater than a pair of states infinitely far away from each other. The 75th percentile of elasticity across all state pairs is about 50 percent larger than the 25th percentile.

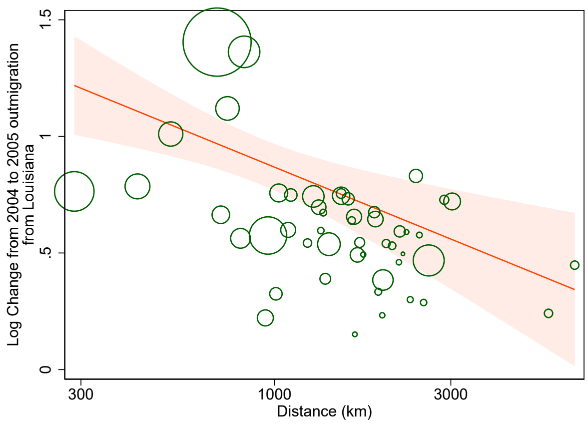
In principle, this is a testable implication. If there were an exogenous shock to a specific state that had no equilibrium impact on the utility of other states, we could see if migration increased more between nearby states than far away states.

However, it is not easy to test the elasticities because many changes in location utility are also correlated across space, either because of correlated underlying shocks or because of equilibrium effects that come through migration or trade.

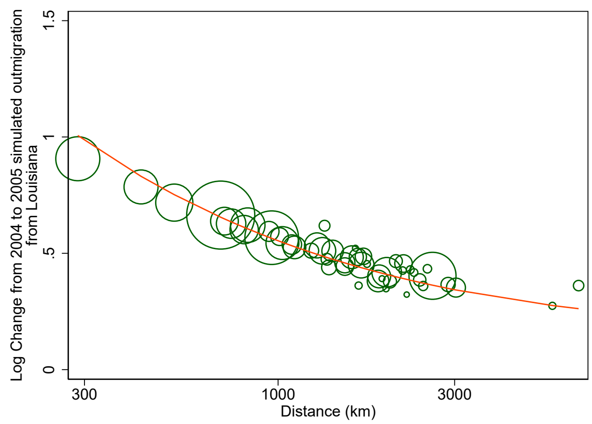
To effectively test this prediction, we explore the Hurricane Katrina shock, which is spatially concentrated in Louisiana and large compared to its potential general equilibrium effects. Arguably, the change in the utility of living in Louisiana after the hurricane was much larger than the spillover effects to nearby states.[13]

We show the log-change in the amount of migration from Louisiana to other states after the hurricane in Figure 6. The left subfigure is the observed data, and the right is the model

[13] We considered other shocks as well, but could not identify large shocks that affected migration significantly in one specific state without spillovers to nearby states. For example, the inmigration to North Dakota during the fracking boom coincided with significant inmigration to South Dakota, and to a less extent, other nearby states as well. Oddly, the abrupt change in migration in Louisiana in 2005 was only on the outmigration side; inmigration responded comparatively little.



(a) Data, with line of best fit



(b) Simulated data, with theoretical approximation line

Figure 6: Outmigration changes, by state, after a five percent decline in Louisiana Population

simulation with a theoretical approximation line. For this exercise, we use the IRS migration data, since the absolute amount of migration between some state pairs is quite small. The log-change in the observed data was larger in closer states, as predicted by the persistent correlated preference model. It is well-publicized that the government aided in moving some displaced migrants to Texas, and the trend is more general than that one point. In addition, the hurricane also hit parts of Mississippi which may explain that outmigration to Mississippi (the furthest left point) was not as high as might be predicted.[14]

In the simulated subfigure, we see that the approximation given by theoretical elasticities $\frac{1}{\sqrt{1-\Sigma_{ij}}}$ is not perfect, but the approximation error is small. To cut down on simulation error, we increase the number of simulated agents to 300 million. Any systemic deviations from the theoretical prediction line are likely due to the fact that ρ is less than one.

[14]Of course, one could think of other explanations for the migration elasticity to vary, based on the public policies affecting the displaced residents or the demographics of the neighborhoods that were affected. We are not claiming that this evidence alone is enough to prefer the persistent correlated preferences model, but we do view the data as consistent with the model's predictions.

3.4 Population elasticities are approximately proportional to the migration matrix

Proposition 4. *In steady-state, as $\rho \to 1$, the derivative of population with respect to the utility of another state is given by*

$$\frac{\partial p_i}{\partial u_j} = \kappa m_{i\to j} \frac{1}{\sqrt{1-\Sigma_{ij}}} \tag{8}$$

when $i \neq j$, for some constant κ. In elasticity terms,

$$\frac{\partial \log p_i}{\partial u_j} = \kappa \frac{m_{i\to j}}{p_i} \frac{1}{\sqrt{1-\Sigma_{ij}}} \tag{9}$$

This proposition is important because it shows the importance of the migration matrix in calculating cross-location population elasticities.

In practice, the variation in migration is orders of magnitudes larger than the variation in the square root of one minus the covariance. So one can say that the population cross-derivative with respect to other utilities is roughly proportional to the migration between the two places. The extra term magnifies this relationship, so that places with more migration have even higher cross-derivatives, but only a little bit.

There are several interesting corollaries to this lesson. The first is that places with higher migration rates have more elastic population to local shocks. For example, D.C. has a gross migration rate of about 10 percent, while states like Michigan, Ohio, New York, and California have gross migration rates below 2 percent. So D.C.'s population is more than five times more elastic to a comparable shock affecting California or Michigan.

Another important corollary is that shocks that are spatially correlated lead to less population movement than shocks that are spatially disparate. We illustrate that with a concrete example in Section 4.

Finally, the population displacement of a shock is spatially concentrated near the location of a shock. This is a short-run feature of dynamic logits as well, but we wish to emphasize it holds in this model as well. The fact that it holds in the long-run as well is our next lesson.

3.5 Short- and long-run population elasticities are the same

A final lesson is that the short- and long-run population elasticities to a permanent change in u_i are the same. The intuition here is simple: the personal preferences have a stationary distribution, so even though people will continue to move, the population of each state only changes when the u_i's change.

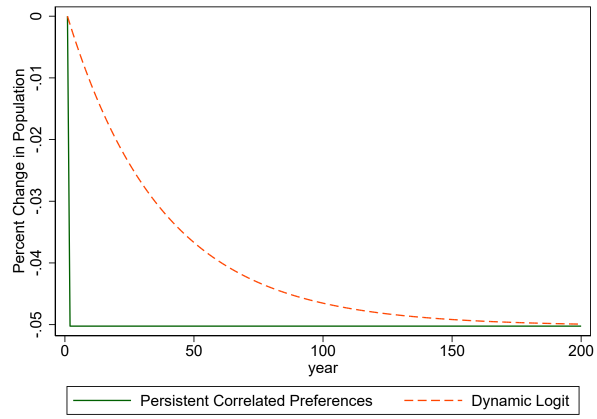
However, this is in sharp contrast to dynamic logit models in the literature, where the short- and long-term effects are quite different. This has important implications because one of the main purposes of the models in this literature is to think about the speed of adjustment (e.g. Liu et al., 2021). Migration, in a dynamic logit model, slows down the speed of adjustment significantly, as after a place gets worse, people will continue to leave once they finally get a low utility draw. Because these draws are independent over time, the adjustment ends up being quite slow. In the persistent correlated preferences model, local utility changes must be persistent for population changes to be persistent.[15]

We illustrate this point by considering the short and long-run effects of a negative permanent shock to one location. Here, we continue to consider Louisiana. We consider a one-time permanent change in the utility of living in Louisiana, and hold all other states constant at their 2004 levels. In Figure 7, we show the dynamics in the persistent correlated preferences model and in the dynamic logit model. We normalize the size of the utility shock separately for each model to have the same long-run population implication in Louisiana. We show the population evolution for Mississippi, because it is close, and New York, because it is far.[16]

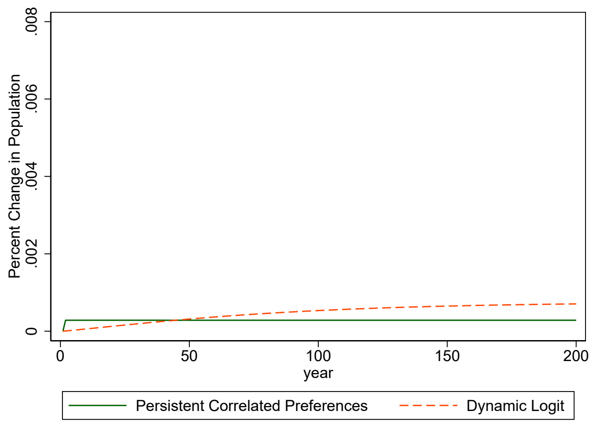
The first thing to notice about the graph is that the population in Louisiana adjusts

[15] Of course, in the data, it is hard to tell how persistent utility is, but the autocorrelation of productivity and amenity shocks, sizable adjustment costs such as the construction of housing, and search costs would all be natural reasons for it to be autocorrelated.

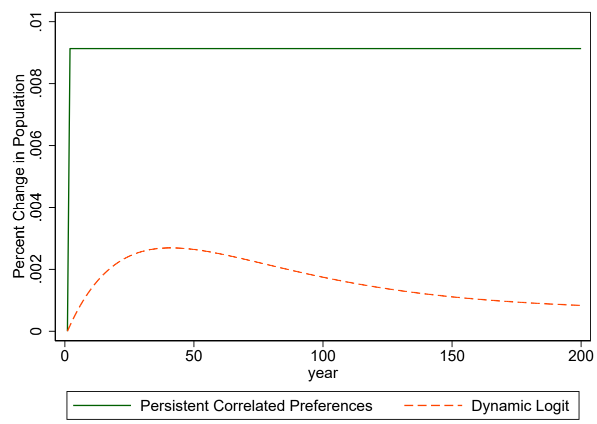
[16] We also chose New York because it large, so we do not need to do as large of a simulation to precisely estimate the elasticity.



(a) Louisiana



(b) New York



(c) Mississippi

Figure 7: Population Dynamics after an MIT-shock to Louisiana utility, normalized to cause a 5 percent long-term decline in Louisiana population

immediately in the persistent correlated preferences model, and very slowly in the dynamic logit model, with a half-life that is several decades long. The second thing to notice is that the effects on other states are also different. For the persistent correlated preferences model, there is a lot more migration to Mississippi than to New York because it is much closer (note that panels (b) and (c) have the same scale). This is also true in the short-run in the dynamic logit model, but the differences die out in the long-run, both because New York continues to grow, and Mississippi initially overshoots the new steady-state population.

Given the difficulties of estimating the long-run effects of a single-location shock on populations in other states, we do not intend Figure 7 as a way to empirically distinguish between the two models. Rather, we wish to emphasize that because these long-run elasticities are so different, that the consequences of getting the model wrong has a significant cost in terms of prediction and counterfactual analysis.

4 Application to the Rust Belt decline

We illustrate the importance of the different cross-elasticities implied by the model by considering the effects of the spatial concentration of the Rust Belt decline since 1980. Over the last several decades, the Rust Belt has experienced stagnant population, largely attributed to the decline in U.S. manufacturing over this time period.[17]

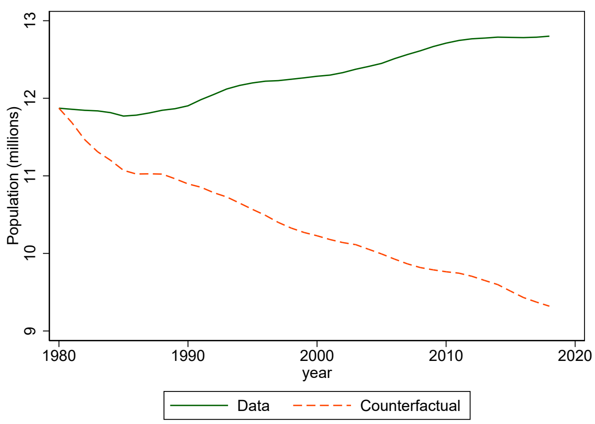
Here, we carry out a counterfactual that demonstrates that the regional concentration of the Rust Belt decline has important implications. We focus on Pennsylvania, as an arbitrarily chosen central Rust Belt state, to make our point.

The counterfactual we wish to consider is what would have happened to Pennsylvania and its people had the same change in utility happened in Pennsylvania, but the rest of the region not been affected. To carry this out, we back out the implied utilities in each year based on the population in each state, and then simulate the model holding the change in Pennsylvania's relative utility the same as in the data, but assuming the rest of the country had kept the same relative utilities as in 1980.

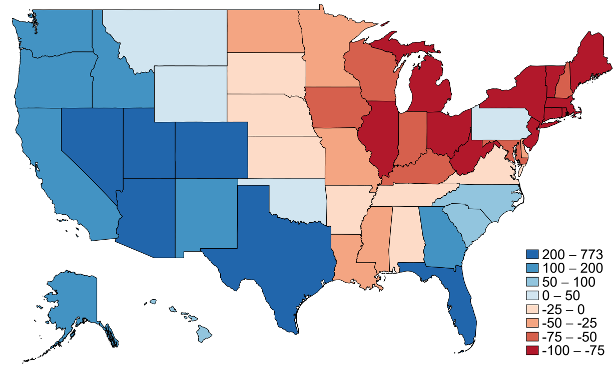
In this model, other Rust Belt states are more substitutable to Pennsylvania, in both the short- and long-run. So the fact that the regions around Pennsylvania are declining at the same time means that the effects of a utility decline of living in Pennsylvania have smaller effects on the population, but larger effects on the utility of people who originally lived there. In other words, the insurance that naturally comes from migration is mitigated when the shocks are regionally concentrated.[18]

[17]While the exact geographic boundaries of the Rust Belt are not universally agreed upon, it is always considered as a contiguous region in the Midwest.

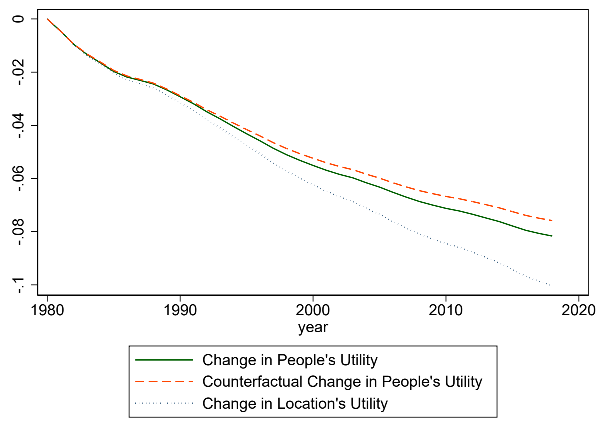
[18]In the counterfactual, the relative utility of Pennsylvania to the average other U.S. state is the same as the data, within each year.



(a) Population Change



(b) Percentage difference by 2018 locations of people who would have lived in Pennsylvania, Counterfactual vs. Data



(c) Utility Change

Figure 8: The Decline of the Rust Belt. Comparison with a counterfactual in which only Pennsylvania's relative utility changed, and the rest of the country's relative utilities are held at constant 1980 levels. Panel (b) shows the percentage difference, by state, of where people who would have lived in Pennsylvania in 2018 if the utilities were the same as in 1980, in the data versus the counterfactual. The percentage difference is calculated as the data divided by the counterfactual, so the red areas have more migrants from Pennsylvania in the counterfactual than the data, and the blue areas have more migrants from Pennsylvania in the data than in the counterfactual. For Panel (c) the dashed line represents the average utility change in the counterfactual of people who would have lived in Pennsylvania had utilities not changed. Hence, the difference between the dashed and dotted lines is the insurance from migration. The solid line is the same, but for the data instead of the counterfactual.

Figure 8 shows the output of this exercise. In the data, the population of Pennsylvania grew slightly over this time period. In the counterfactual, the population declines significantly (Figure 8a).[19] Looking at the map in Figure 8b, we can see that those people would

[19]The total population of the United States is exogenous in the model, and proportions of that population choose to live in different states based on their idiosyncratic utility. The share of population living in Pennsylvania declined in both the data and the counterfactual.

have moved to nearby Rust Belt states had they not also been in decline. The map shows the percent difference in the number of people who would have lived in Pennsylvania under constant utility, but live in other states because Pennsylvania's utility declined. Because of the decline of the Rust Belt, in the data compared to the counterfactual, more people moved to places in the West and the South, but also a significant number stayed in Pennsylvania.

Looking at the implied utilities, one can see how much of the insurance that comes from migration is eroded when utility changes are spatially correlated. In Figure 8c, the dotted line is the implied decline in utility for the state of Pennsylvania. The solid line is the decline in utility for the average person who would have lived in Pennsylvania had the utility stayed the same. And the dashed line is the decline in utility for the average person who would have lived in Pennsylvania, in the counterfactual. The average utility decline in the counterfactual is only about two-thirds as large as the direct effect on Pennsylvania's utility, i.e. 32 percent of the utility decline is insured by migration if Pennsylvania is the only state receiving a shock. However, with the utilities implied by the data, the rest of the region been affected, fewer people migrate out, and only about 24 percent of the shock is insured. So while migration is still providing meaningful insurance, the insurance is roughly 25 percent smaller because of the spatial concentration of the Rust Belt decline.

This counterfactual leaves out many important features of spatial models, notably any role for higher population causing lower wages, higher rents, or changes in amenities. The reason for this is to focus on the lessons learned from the migration part of the model. However, in Appendix D, we consider the counterfactual with a congestion force, and show the insurance results are similar, even though population differences are smaller.

5 Conclusion

We propose a new model of migration that can generate a gravity relationship and match realistic migration dynamics. We show that this model has important implications for spatial economics models. In particular, the migration matrix is informative regarding the long-run population cross-elasticities. And the dynamics of population are quite different than typical dynamic logit models.

We use the decline of the Rust Belt to show one lesson from our model: that the population dynamics and welfare implications of a utility change depend crucially on how spatially correlated the shock is.

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A Proofs

A.1 Proof of Proposition 1

If $f(x) = \exp(-a\sqrt{x})$ is completely monotone and non-constant, then Σ is positive definite by the Schoenberg Interpolation Theorem (Schoenberg, 1938).[20] f is clearly non-constant, so it remains to show that $f(x)$ is completely monotone. Note that $\exp(-ax)$ is completely monotone. Note also that $\sqrt{x}$ is a Bernstein function, meaning that its derivative is completely monotone. The composition $g(h(x))$ of a completely monotone function g and a Bernstein function h is completely monotone (Sandev and Tomovski, 2019). Therefore, $\exp(-a\sqrt{x})$ is completely monotone. $\square$

A.2 Proof of Proposition 2

Consider people who are living in i, but close to indifferent between living in i and j (As $\rho \to 1$, the number of people that might move between three places, as percentage of those that might move to two places, diminishes to zero). A person moves from i in year 0 to j in year t if $u_{in0} > u_{jn0}$ but $u_{jnt} > u_{int}$. By the recursive nature of the utility shocks,

$$u_{int} - u_{jnt} = u_{i0} - u_{j0} + \rho^t(\epsilon_{in0} - \epsilon_{jn0}) + \sum_{s=1}^{t} \rho^{t-s}\sqrt{1-\rho^2}(\eta_{ins} - \eta_{jns}) \tag{10}$$

The distribution of the shocks over t periods are given by

$$\sum_{s=1}^{t} \rho^{t-s}\sqrt{1-\rho^2}\eta_{ns} \sim N\left(0, (1-\rho^{2t})\Sigma\right) \tag{11}$$

[20]A function $f : [0,\infty) \to [0,\infty)$ is completely monotone if it is smooth and $(-1)^k f^{(k)}(x) \geq 0$ for all $x > 0$ and $k \in \mathbb{N}$.

The Schoenberg Interpolation Theorem states that if f is completely monotone and not constant, then for any distinct points $x_1, ...x_n$ in any real inner product space the $n \times n$ matrix A defined by $A_{ij} = f(||x_i - x_j||^2)$ is positive definite.

So for a given utility difference $u_{in0} - u_{jn0}$, the probability that person moves to j in t is

$$1 - \Phi\left(\frac{u_{i0} - u_{j0} + \rho^t(\epsilon_{in0} - \epsilon_{jn0})}{\sqrt{1-\rho^{2t}}\sqrt{2-2\Sigma_{ij}}}\right) \tag{12}$$

where Φ is the standard normal cumulative density function.

Define $F_{ij}(\epsilon)$ to be the mass of people that have $\epsilon_{in0} - \epsilon_{jn0} = \epsilon$. Note that this is continuous and bounded. Then the total number of migrants over t years is

$$\int_{u_{j0}-u_{i0}}^{\infty} F_{ij}(\epsilon)\left(1 - \Phi\left(\frac{u_{i0} - u_{j0} + \rho^t \epsilon}{\sqrt{1-\rho^{2t}}\sqrt{2-2\Sigma_{ij}}}\right)\right) d\epsilon \tag{13}$$

or with a simple u substitution,

$$\frac{1}{\rho^t}\sqrt{1-\rho^{2t}}\sqrt{2-2\Sigma_{ij}} \int_{-\infty}^{\frac{(1-\rho^t)(u_{j0}-u_{i0})}{\sqrt{1-\rho^{2t}}\sqrt{2-2\Sigma_{ij}}}} F_{ij}\left(\frac{-1}{\rho^t}(w\sqrt{1-\rho^{2t}}\sqrt{2-2\Sigma_{ij}} - (u_{j0} - u_{i0}))\right)\Phi(w)\,dw \tag{14}$$

Dividing by when $t = 1$, this quantity is

$$\frac{1}{\rho^{t-1}}\sqrt{\frac{1-\rho^{2t}}{1-\rho^2}} \frac{\int_{-\infty}^{\frac{(1-\rho^t)(u_{j0}-u_{i0})}{\sqrt{1-\rho^{2t}}\sqrt{2-2\Sigma_{ij}}}} F_{ij}\left(\frac{-1}{\rho^t}(w\sqrt{1-\rho^{2t}}\sqrt{2-2\Sigma_{ij}} - (u_{j0} - u_{i0}))\right)\Phi(w)\,dw}{\int_{-\infty}^{\frac{(1-\rho)(u_{j0}-u_{i0})}{\sqrt{1-\rho^{2}}\sqrt{2-2\Sigma_{ij}}}} F_{ij}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^{2}}\sqrt{2-2\Sigma_{ij}} - (u_{j0} - u_{i0}))\right)\Phi(w)\,dw} \tag{15}$$

To take the limit as $\rho \to 1$, we can evaluate various terms separately:

$$\begin{aligned}
\lim_{\rho\to 1}\frac{1}{\rho^{t-1}} &= 1 \\
\lim_{\rho\to 1}\sqrt{\frac{1-\rho^{2t}}{1-\rho^2}} &= \sqrt{t} \\
\lim_{\rho\to 1}\frac{(1-\rho^t)(u_{j0}-u_{i0})}{\sqrt{1-\rho^{2t}}\sqrt{2-2\Sigma_{ij}}} &= 0 \\
\lim_{\rho\to 1}\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}} - (u_{j0} - u_{i0})) &= u_{j0} - u_{i0}
\end{aligned}$$

where the second line is by applying L'Hôpital's rule to the interior of the square root, and the third line can be obtained similarly, by moving the numerator into the square root, and applying L'Hôpital's rule. So the whole limit is

$$\sqrt{t}\frac{F_{ij}(u_{j0}-u_{i0})\int_{-\infty}^{0}\Phi(w)dw}{F_{ij}(u_{j0}-u_{i0})\int_{-\infty}^{0}\Phi(w)dw}=\sqrt{t} \tag{16}$$

The F term can be pulled out because F_{ij} is continuous and bounded and $\lim_{w\to-\infty}\Phi(w)=0$. Therefore, the ratio of migration over t periods to migration over 1 period converges to $\sqrt{t}$. □

A.3 Proof of Proposition 3

As in the proof of proposition 2, for a given utility difference $\epsilon_{in0}-\epsilon_{jn0}$, the probability that person moves to j in $t=1$ is

$$1-\Phi\left(\frac{u_{i0}-u_{j0}+\rho(\epsilon_{in0}-\epsilon_{jn0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}\right) \tag{17}$$

where Φ is the standard normal cumulative density function.

If u_{j0} changes to u'_{j1}, then

$$1-\Phi\left(\frac{u_{i0}-u'_{j1}+\rho(\epsilon_{in0}-\epsilon_{jn0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}\right) \tag{18}$$

Define $F_{ij}(\epsilon)$ to be the mass of people that have $\epsilon_{in0}-\epsilon_{jn0}=\epsilon$. Note that this is continuous and bounded. Then the total migration from i to j is

$$\int_{u_{j0}-u_{i0}}^{\infty}F_{ij}(\epsilon)\left(1-\Phi\left(\frac{u_{i0}-u'_{j1}+\rho\epsilon}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}\right)\right)d\epsilon \tag{19}$$

Taking a derivative with respect to u'_{j1},

$$\frac{\partial m_{ij}}{\partial u'_{j1}}=\frac{1}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}\int_{u_{j0}-u_{i0}}^{\infty}F_{ij}(\epsilon)\phi\left(\frac{u_{i0}-u'_{j1}+\rho\epsilon}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}\right)d\epsilon \tag{20}$$

Evaluating it at $u'_{j1} = u_{j0}$,

$$\frac{\partial m_{ij}}{\partial u'_{j1}} = \frac{1}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}} \int_{u_{j0}-u_{i0}}^{\infty} F_{ij}(\epsilon)\phi\left(\frac{u_{i0}-u_{j0}+\rho\epsilon}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}\right) d\epsilon \tag{21}$$

Making a u-substitution,

$$\frac{\partial m_{ij}}{\partial u'_{j1}} = \frac{1}{\rho}\int_{-\infty}^{\frac{(1-\rho)(u_{j0}-u_{i0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}} F_{ij}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}-(u_{j0}-u_{i0}))\right)\phi(w)\,dw \tag{22}$$

And dividing by the overall migration (with the same u-substitution),

$$\frac{1}{m_{ij}}\frac{\partial m_{ij}}{\partial u'_{j1}} = \frac{1}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}} \frac{\int_{-\infty}^{\frac{(1-\rho)(u_{j0}-u_{i0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}} F_{ij}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}-(u_{j0}-u_{i0}))\right)\phi(w)\,dw}{\int_{-\infty}^{\frac{(1-\rho)(u_{j0}-u_{i0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}} F_{ij}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}-(u_{j0}-u_{i0}))\right)\Phi(w)\,dw} \tag{23}$$

The ratio of the elasticity to another elasticity, but between k and ℓ instead of i and j is given by:

$$\frac{\frac{1}{m_{ij}}\frac{\partial m_{ij}}{\partial u'_{j1}}}{\frac{1}{m_{k\ell}}\frac{\partial m_{k\ell}}{\partial u_{\ell 1}}} = \frac{\frac{1}{\sqrt{1-\Sigma_{ij}}}\frac{\int_{-\infty}^{\frac{(1-\rho)(u_{j0}-u_{i0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}} F_{ij}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}-(u_{j0}-u_{i0}))\right)\phi(w)dw}{\int_{-\infty}^{\frac{(1-\rho)(u_{j0}-u_{i0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}} F_{ij}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}-(u_{j0}-u_{i0}))\right)\Phi(w)dw}}{\frac{1}{\sqrt{1-\Sigma_{k\ell}}}\frac{\int_{-\infty}^{\frac{(1-\rho)(u_{\ell 0}-u_{k0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{k\ell}}}} F_{k\ell}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{k\ell}}-(u_{\ell 0}-u_{k0}))\right)\phi(w)dw}{\int_{-\infty}^{\frac{(1-\rho)(u_{\ell 0}-u_{k0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{k\ell}}}} F_{k\ell}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{k\ell}}-(u_{\ell 0}-u_{k0}))\right)\Phi(w)dw}} \tag{24}$$

And the limit as $\rho \to 1$,

$$\lim_{\rho\to 1}\frac{\frac{1}{m_{ij}}\frac{\partial m_{ij}}{\partial u'_{j1}}}{\frac{1}{m_{k\ell}}\frac{\partial m_{k\ell}}{\partial u_{\ell 1}}} = \frac{\frac{1}{\sqrt{1-\Sigma_{ij}}}}{\frac{1}{\sqrt{1-\Sigma_{k\ell}}}} \tag{25}$$

So the semi-elasticity of migration from i to j with respect to u_j is proportional to $\frac{1}{\sqrt{1-\Sigma_{ij}}}$. $\square$

A.4 Proof of Proposition 4

From equation (14) in the proof of Proposition 2,

$$m_{ij} = \frac{1}{\rho}\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}} \int_{-\infty}^{\frac{(1-\rho)(u_{j0}-u_{i0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}} F_{ij}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}} - (u_{j0}-u_{i0}))\right) \Phi(w)\, dw \tag{26}$$

So the ratio of migration is given by

$$\frac{m_{ij}}{m_{k\ell}} = \frac{\sqrt{2-2\Sigma_{ij}} \int_{-\infty}^{\frac{(1-\rho)(u_{j0}-u_{i0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}}}} F_{ij}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{ij}} - (u_{j0}-u_{i0}))\right) \Phi(w)\, dw}{\sqrt{2-2\Sigma_{k\ell}} \int_{-\infty}^{\frac{(1-\rho)(u_{\ell 0}-u_{k0})}{\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{k\ell}}}} F_{k\ell}\left(\frac{-1}{\rho}(w\sqrt{1-\rho^2}\sqrt{2-2\Sigma_{k\ell}} - (u_{\ell 0}-u_{k0}))\right) \Phi(w)\, dw} \tag{27}$$

So as $\rho \to 1$, this approaches

$$\lim_{\rho\to 1} \frac{m_{ij}}{m_{k\ell}} = \frac{\sqrt{1-\Sigma_{ij}} F_{ij}(u_{j0}-u_{i0})}{\sqrt{1-\Sigma_{k\ell}} F_{k\ell}(u_{\ell 0}-u_{k0})} \tag{28}$$

By the definition of F, the change in population is

$$\frac{\partial p_i}{\partial u_j} = -F_{ij}(u_{j0}-u_{i0}) \tag{29}$$

So as $\rho \to 1$,

$$\frac{\partial p_i/\partial u_j}{\partial p_k/\partial u_\ell} = \frac{m_{ij}/\sqrt{1-\Sigma_{ij}}}{m_{k\ell}/\sqrt{1-\Sigma_{k\ell}}} \tag{30}$$

Therefore, there exists a κ such that

$$\frac{\partial p_i}{\partial u_j} = \kappa \frac{m_{ij}}{\sqrt{1-\Sigma_{ij}}} \tag{31}$$

□

B Parametrization Details

In this appendix, we go over the procedure used to parametrize the model. As explained in the main text, the goal is to match the distance coefficient in a standard gravity equation, the population of each state, and the overall migration rate. In the baseline model, the parameters are a, which governs the spatial correlation of preferences; ρ which governs the persistence of preferences; and the u_i's which govern the desirability of each location.

Here is an overview of the procedure, with details below.

1. Guess an a.
2. Given that a, find the u_i that generate the populations in period 1.
3. Given that a and the u_i, find ρ that matches the migration rate.
4. Run a gravity regression and update the guess of a, and go back to step 2.

For step 2, we rely on an approximation in the proof of Proposition 4.

$$\frac{\partial p_i}{\partial u_j} \approx \rho \frac{1}{\sqrt{1-\rho^2}} \frac{1}{\sqrt{2-\Sigma_{ij}}} m_{ij}$$

We start with an initial guess for the vector of u_i's and use any number close to 1 for rho,[21] simulate two periods of the model with 10 million people,[22] add up the m_{ij}'s in the simulation, and then calculate the approximate cross-partials. With the cross-partials, we can calculate the change in the u_i's needed to hit the target population if their relationship was linear. Of course, the matrix of cross-partials is not invertible since the u_i's are only meaningful relative to one another. So we normalize $u_1 = 0$. We update the other u_i's based on inverting an $I-1$ by $I-1$ matrix of the $\partial p_i / \partial u_i$ times the vector of how far the

[21] In practice, we use zeros for u_i in the first two iterations, and for future iterations, we use the previous iteration's solution for u_i.

[22] To do a simulation, we simply draw 10 million random multivariate normals, with covariance Σ, add the u_i's, find the maximum for each, then simulate the second period by drawing a new 10 million random numbers, and adding them together based on ρ. Migration is calculated by counting the number of the draws that ended up with a person living in i in period 1 and j in period 2.

populations in the simulation were from the populations in the data. We repeat this until each state's population is within one-tenth of one percent of the data, which typically takes a couple of iterations.

For step 3, we use the fact that migration is approximately proportional to $\sqrt{1-\rho^2}$. So we guess a ρ, simulate the model, find the migration rate in the simulation, and then scale ρ in order to hit the true migration rate.[23] We iterate until the migration rates is within one-hundredth of a percent. This typically takes 1 or 2 iterations.

For step 4, we use a bisection procedure. We store a "too-high" guess for a which generates too little of a relationship between distance and migration, and a "too-low" guess for a, which generates too strong of a relationship. Our next guess is the geometric mean of the two guesses, and depending on the gravity coefficient at the end, we replace either our "too-high" or "too-low" guess with the previous guess. We repeat this loop until we match the gravity distance coefficient to four digits.

C Measuring distance more generally

There are other determinants of migration flows besides distance and population. In our baseline model, we only try to match the gravity coefficient on distance, but in this appendix, we demonstrate the versatility of the model.

One fact about migration is that people move more between similarly-educated regions. One reason for this is that people may have correlated preferences over the amenities that are present in educated areas.[24]

In fact, if we run a gravity equation with one extra term, the "distance" in terms of

[23]The formula for this is $\rho_{\text{new}} = \sqrt{1-(1-\rho_{\text{old}}^2)\frac{m_{\text{data}}}{m_{\text{simulation}}}^2}$.

[24]Another possibility is that the high-skill and low-skill workers have different preferences over where to live. This is totally plausible, but it is straightforward to incorporate into the model by explicitly modeling the heterogeneity, so there is no need to do the exercise we carry out in this section.

	(1) Migration (Credit)	(2) Simulated Migration (with Education)	(3) Simulated Migration
Log Distance	-0.741***	-0.741***	-0.741***
	(0.0503)	(0.0382)	(0.0388)
Abs. Diff. in Bachelor's Deg. Share'	-2.485**	-2.485***	-2.375***
	(0.895)	(0.506)	(0.533)
Log Destination Population	0.879***	0.879***	0.876***
	(0.0794)	(0.0491)	(0.0496)
Log Origin Population	0.909***	0.878***	0.879***
	(0.0796)	(0.0479)	(0.0481)
Observations	2550	2550	2550
Pseudo R^2	0.722	0.907	0.906

Standard Errors are two-way clustered by origin and destination states

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1: An extension to the gravity equation

education matters significantly. We run the following Poisson regression:

$$\log m_{i \to j} = \alpha \log p_i + \gamma \log p_j - \beta \log \text{distance}_{ij} - \delta |\text{Bachelor's share}_i - \text{Bachelor's share}_j| + \epsilon_{ij} \tag{32}$$

where Bachelor's share$_i$ is the share for the 25 and older with a bachelor's degree or higher in the 2000 Census (Manson, Schroeder, Riper, Kugler and Ruggles, 2021). The results of this regression are in column (1) of Table A1. The coefficient on the absolute difference in the bachelor's share is negative and statistically significant.

Can our model capture this determinant of migration? The challenge is to make locations with similar bachelor's degree shares more correlated while continuing to ensure that the covariance matrix is positive definite. By proposition 1, we know that as long as we are measuring a distance in $\mathbb{R}^n$, then the matrix is still positive definite. The solution is to make the education level another dimension:

$$\text{distance}_{ij} = \sqrt{\text{physical distance}_{ij}^2 + b(\text{education level}_i - \text{education level}_j)^2} \tag{33}$$

where b is another parameter to estimate. We will aim to also match δ from the Poisson regression coefficient, in addition to the gross migration rate and β, which we were already aiming to match.

The parameters we calibrate are $\rho = .999623$, $a = -.025044$ and $\sqrt{b} = 908.4$.[25] We show $\sqrt{b}$ because it has a geometric interpretation: it is like imagining that for every 1 percent higher share of bachelor's degrees, the state's location is displaced 9.04 kilometers vertically.

We show the Poisson regression of the model including b in column (2) of Table A1. We are able to match the targeted coefficients to three decimal places. The population coefficients, which are not targeted, are again fairly close.

Interestingly, in column (3), the original parametrization from Table 1, where $b = 0$, also does a fairly good job of matching the education coefficient. Likely, this is because much of what the education coefficient is capturing is the non-linear effects of distance (e.g. excess movement between California and Massachusetts). And we already know from Figure 2 that the baseline model can capture that non-linearity. Nonetheless, the difference in the psuedo-r^2s suggest that the model with education is picking up important additional variation in migration.

D Rust Belt application with congestion

In this appendix, we extend the counterfactual studied in Section 4 to include a congestion force. In many urban models, this would take the form of decreasing wages or increasing rents as the population grows. In this paper, the point of the model is not to microfound the congestion force, it is to demonstrate that the conclusions are robust to realistic features that are common in many other models.[26]

Here, we assume that the congestion force takes on the functional form:

$$u_{it} = \bar{u}_{it} - \kappa \log \text{Population}_i \tag{34}$$

[25]We actually calibrate a^2/b^2 in the code for computational purposes, so that a has less of an effect on the importance of the education difference.

[26]It is not settled in the literature that raising population lowers utility, as there is a large literature pointing out that there are significant agglomeration benefits in terms of wages and amenities, and they may outweigh any increase in housing costs.

We adopt this form for a couple of reasons. κ can easily be interpreted as a congestion elasticity. And if the population grows uniformly everywhere, it does not affect the relative utilities. It also clearly nests the counterfactual in section 4 by setting $\kappa = 0$. It can also accommodate net agglomeration, although we do not show that here.

We keep the rest of the model the same. We can solve for the $\bar{u}_{it}$ the same way as we do in Section 4. Then to solve the model, we look for a fixed point between the utilities and the population of each state in each period.

In Figure A1, we show the results of this new counterfactual, where we set $\kappa = 0.5$. Recall that in the counterfactual we are keeping the relative utility of all states except Pennsylvania constant from 1980-2018, while still allowing a decline in Pennsylvania. The biggest difference from section 4 is in Figure A1a, where the difference in population between the data and counterfactual is much smaller. However, in both counterfactuals, more people are staying in the Rust Belt, and more people are leaving Pennsylvania, just the magnitudes are a bit smaller when we have a congestion force.

Critically, the results on the utility are not that different. In this case, the decline of the Rust Belt wipes out about 16 percent of the insurance from migration, slightly smaller than the 25 percent change in section 4.

E Dynamic Logit Model

Throughout the paper, we compare simulations of the persistent correlated preferences model to a standard dynamic logit model which we present here.

As in the main model, individuals are denoted by n and locations by i. An agent that lived in j at $t-1$ has utility:

$$u_{nt}(j) = \max_i u_{int} = \max_i u_{it} - \delta_{ij} + \epsilon_{ijt} \tag{35}$$

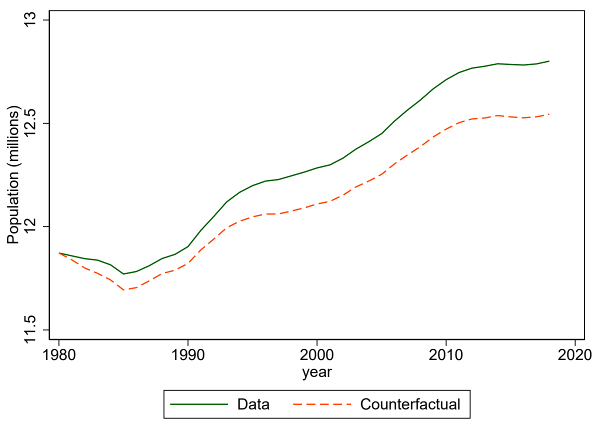
where u_{it} is the baseline utility of living in i, δ_{ij} is the bilateral moving cost between i and j, and ϵ_{ijt} is an independent and identically distributed random variable with an extreme-value distribution. We assume ϵ_{ijt} has a Gumbel distribution with scale parameter 1. In this case,

$$\frac{m_{i \to j,t}}{p_{it}} = \frac{e^{u_{jt} - \delta ij}}{\sum_k e^{u_{kt} - \delta_{ik}}} \tag{36}$$

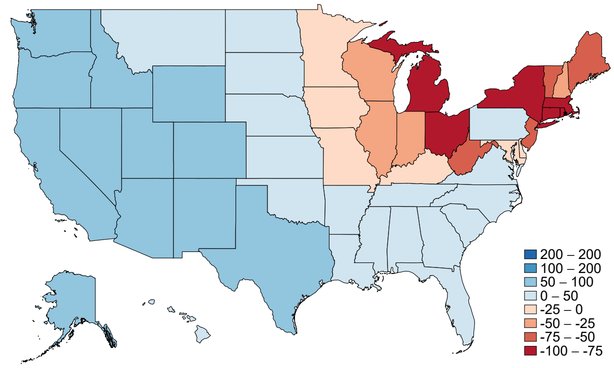
where δ_{ii} is normalized to 1.

Note that the agents in this model are myopic. This avoids the feature of these models that location i becomes more desirable if it has lower moving costs to an actually desirable location j.

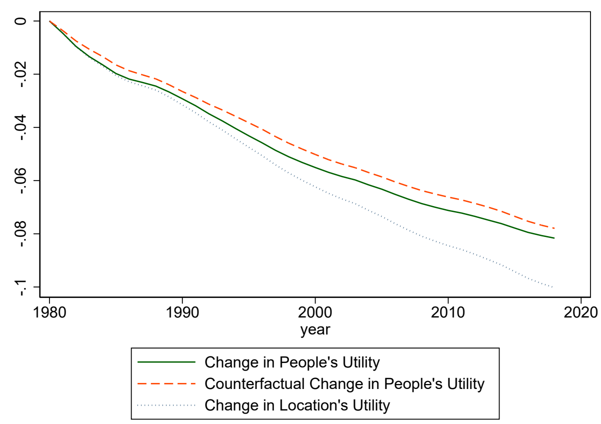
Under these assumptions, the probability of moving to any specific location depends only on the current location. In other words, location is a Markov chain. Throughout the paper, we calibrate the δ's and u's to match the 2004 migration matrix. We adjust the matrix by taking the average number of migrants from i to j and from j to i and assign it to both directions, such that the economy is in a steady-state. This makes the dynamic logit model more comparable to the persistent correlated preferences model.



(a) Population Change



(b) Percentage difference by 2018 locations of people living in Pennsylvania in 1980, Data vs. Counterfactual



(c) Utility Change

Figure A1: The Decline of the Rust Belt. Comparison with a counterfactual in which only Pennsylvania's relative utility changed, and the rest of the country's relative utilities are held at constant 1980 levels. The counterfactual includes a congestion force. Panel (b) shows the percentage difference, by state, of where people who would have lived in Pennsylvania in 2018 if the utilities were the same as in 1980, in the data versus the counterfactual. The percentage difference is calculated as the data divided by the counterfactual, so the red areas have more migrants from Pennsylvania in the counterfactual than the data, and the blue areas have more migrants from Pennsylvania in the data than in the counterfactual. For Panel (c) the dashed line represents the average utility change in the counterfactual of people who would have lived in Pennsylvania had utilities not changed. Hence, the difference between the dashed and dotted lines is the insurance from migration. The solid line is the same, but for the data instead of the counterfactual.