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Pandemic Politics: Tiebout Sorting and Work-From-Home

Jack Taylor

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Abstract

Where to live and when to move are two fundamental questions people have to answer in their lives. People weigh their preferences for what jurisdictions offer and choose the best mix of wages, amenities, and, importantly, public policies and politics. However, employment constraints and mobility costs mean that people have to make concessions about where to live. Importantly, people may live in a place orthogonal to their personal politics in order to have a good job and high-quality amenities. Using a novel data set from the COVID-19 pandemic, this paper answers the question of what people do when they no longer have to entertain the costs of moving. Using a simple theoretical model, this paper arrives at the conclusion that when origins and destinations differ by amenities, people will sort along political lines under a work-from-home regime. The theory also predicts that when origins and destinations differ by productivity, there will not be political sorting under work-from-home. Work-from-home allowed people to retain their jobs and move cheaply, and the pandemic was a time of heightened political salience. These factors, combined with the nature of a pandemic, allowed for a natural experiment framework. This, in turn, gives rise to novel empirical results, the most important of which, is that there has been an increase in political sorting in the US, and has only increased since the COVID-19 pandemic started. Further results show that in the case of an amenity differential, the theory is corroborated by the data, and there are no significant results for a productivity differential.

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†Clemson University, then Federal Reserve Bank of Richmond

1 Introduction

This paper investigates the influence of politics on migration induced by the COVID-19 pandemic. To guide an empirical analysis, I develop a theoretical model that explains how declining mobility costs stemming from work-from-home changes the heterogeneity of beliefs across cities. My model arrives at a definitive result regarding political Tiebout sorting. Using a novel data set that comprises migration between 76 pairs of Combined Statistical Areas across 21 quarters from 2017-2022, I modify a baseline linear model with a triple difference approach. The key findings of this paper are that, under a work-from-home regime, theory predicts increased political sorting under differentiated amenities but under differentiated productivity. Empirically I find significant evidence for political sorting under differentiated amenities and an increase in political sorting post-COVID-19 relative to before the pandemic; I do not find significant evidence to address the question of political sorting under differentiated productivity.

The theoretical model builds on a long line of research inspired by Tiebout's 1965 article about competition in public good provision between cities, the so-called voting by your feet phenomenon. My model builds most directly on the work of Rhode and Strumpf and Kaplan et. al., who study Tiebout's hypothesis through the lens of declining mobility costs and geographic political polarization. The key contribution of this paper is a unified theoretical and empirical approach to studying Tiebout sorting under a setting with low mobility costs and increased political salience. Ancillary contributions come from the construction of a novel data set, the most comprehensive ranking of Combined Statistical Areas by amenities, and a visualization of the estimated Hicksian demand for amenities.

The COVID-19 pandemic provided an exemplary setting to answer the question of what drives people's migration decisions. The presence of the migration cost constraint means that people have to consider economic feasibility when moving; either moving shorter distances or choosing the location that was the utility maximizer given their constraints, but not their optimal location. The pandemic, resulting in the rise of work-from-home, saw a decrease in the costs of moving. People were faced with lower moving equipment costs and ease of rental and no longer had to be concerned with finding jobs in new locations. Thanks in large part to the advances in video conference technology, work from home has become a more permanent fixture in the gig economy even after rollbacks of closures and expanded vaccination rates. The COVID-19 pandemic also was a time of increased political salience. Everything became politicized, and polarization spread across many facets of daily life. Mask mandates, vaccine rhetoric and mandates, and school and business closures made it nearly impossible to escape politics. Thus, the natural experiment framework from the pandemic, along with high political salience and low mobility costs, was the perfect setting to study this question.

The data used in this paper is that of a novel, self-assembled data set. I made use of data compiled by Redfin's Data Center, the MIT Election Lab, and The United States Census.

I compiled and matched this data set such that for each origin Combined Statistical Area and each destination Combined Statistical Area, I defined variables for partisanship, population, migration, income, and home prices. It was important to work in pairs, so I made a variable that explicitly matched each origin and destination together in each quarter with the appropriate data. The data was organized such that each entry was all of the political, income, price, and migration data for a unique origin and destination pair at a unique time. This allowed me to run a straightforward linear model as well as modifications that made use of categorical variables that partitioned the data by time and by amenity and productivity differences.

The theoretical results predict that, when origin and destination locations differ along amenities, we will observe political sorting. They further predict that when they differ by productivity, we will not see evidence of political sorting. More nuanced results are that origins and destinations that differ along amenities will see an increase within Combined Statistical Area political heterogeneity, whereas those which differ along productivity will see a decrease. Empirically the results are mixed. There is significant evidence that we do observe political sorting between origins and destinations that differ in amenities, but there is no significant evidence that we do not see this effect in origin-destination pairs that differ in productivity. Empirically it is also demonstrated that as the COVID-19 pandemic continued, there is an increase in political sorting overall for all origin and destination pairs.

The results of this paper make a fundamental and novel contribution to the literature. There has been a dearth of papers that address migration during the COVID-19 pandemic; much fewer seek to address the effect that the polarization of the pandemic has had on people. The closest anyone has come to studying this has been Rhode and Strumpf, what happens in a Tiebout sorting model with falling mobility costs, and Kaplan et. al., what is the state of political polarization from a geographic perspective? This paper presents several novel theoretical and empirical results that aim to carve a niche in the literature and be the impetus for others seeking to study political Tiebout sorting, mobility costs, and migration effects of COVID-19.

2 Existing Literature

The model presented in this paper builds off of the literature founded by Charles Tiebout's 1956 article on spatial sorting across jurisdictions. Tiebout's hypothesis, while greatly influential, has been roundly criticized for its assumptions, especially the assumptions of costless migration. The model contained in this paper analyzes Tiebout's hypothesis in a setting that more closely mirrors his assumed world than any work yet. It further continues and unifies the work of two articles that address the criticisms of Tiebout's model and turn the results into a modern setting. Rhode and Strumpf in 2002 and Kaplan et. al. in 2022 present different interpretations of Tiebout's hypothesis; one analyzes sorting under falling mobility costs, and the other considers geographic political sorting. This paper continues and unifies their models and results while addressing the criticisms of Tiebout's model in a newer and more experimentally friendly environment.

The hypothesized existence of spatial sorting dates back to Charles Tiebout's "A Pure Theory of Local Expenditures", a 1956 Journal of Political Economy Article. In this seminal article, Tiebout likens localities and public goods to a market, insofar as competition between locales for residents will lead to the equilibrium provision of public goods for the type, or preferences, of the residents (Tiebout 1956). Tiebout sees this framework as a means of tackling and solving the problem of public goods provision, as Samuelson and Musgrave see it. His hypothesis, multiple modifications, and the results of his model have been roundly tested and verified as well as criticized[1] (Alesina, Baqir, and Hoxby 2004, Bewley 1981, Epple, Romer, and Sieg 1999, Epple and Sieg 1998, Glaeser, Rosenthal, and Strange 2009, Glaeser and Ward 2006, Kollman, Miller, and Page 1997, Rhode and Strumf 2002, & Stiglitz 1982.).

Tiebout's paper says that a local government faces a fork and can pursue two tactics to gain more residents and reach the optimal city size Tiebout claims exists. Cities can either engage in cartel-like behavior and collude to institute a uniform tax rate across all communities; or, they can engage in tax competition. Tiebout argues that regardless of the road pursued, the end result will be the same.

The idea of tax competition, as it is now called in the local public finance literature, is more of a revenue-expenditure scheme. Local governments compete for residents to increase their tax base. They do this in a manner of taxing and spending. They must raise revenue to fund expenses, namely public goods. Meltzer and Richard in 1981 add a layer of depth to this assertion.

Each person is utility-maximizing and seeks the combination of work, leisure, and consumption in the standard consumer problem way (Meltzer and Richard, 1981). Further, citizens are fully informed about the size of the government, meaning they have perfect information regarding the tax rate and spending levels in each locale they consider moving to.

Thus, it is the role of the government to balance growth and redistribution. The more people that a city attracts, the more tax revenue they accrue; but, there will be increased demands for redistribution. In the explicit language of the Tiebout model, this market-like competition between cities is to attract the most citizens insofar as the provision of public goods is done at the minimum cost level. This is the mechanism by which Tiebout's assumption that an optimal city size exists manifests.

In this analysis, we implicitly assume majoritarian decision-making, so the median

[1] I address the criticisms later in this section.

member of the city is the deciding vote. In other words, the type of the median voter in a city reflects the "type" of the city. Voters with income lower(higher) than that of the median prefer high(low) redistribution and high(low) tax cities, and the scope of the government (taxing and spending) rises(falls) as income rises(falls). The income of the median voter can be considered their type, and the lower(higher) it is relative to the mean means the majority of the mass falls in the high(low) scope of government range.

If the median voter in city A has a relatively low(high) income, then city A will have an expansive(limited) scope of government, and with it, a high(low) tax rate and a high(low) level of public good expenditure. This makes the city attractive for people not living in City A who are to the left(right) of the median voter in City A. Hence, those residents appropriately positioned will move to city A and those not will move away to another city.

As I discuss in depth in 3.5, the above analysis is easily generalized beyond public goods to any public policy or a vector of public policies, and the results still hold. I now turn to the case of Kaplan et. al., who do generalize this to public policies.

Kaplan, Spenkuch, and Sullivan, in a 2022 Journal of Public Economics article, consider the case of sorting by utility-maximizing citizens with utility defined, in part, over political heterogeneity in a city. In their article, they construct a variance-like index of heterogeneity in the partisanship of a geographic location and apply it to a panel of US states from 1970-2016 (Kaplan et. al., 2022).

The innovative approach leads the authors to arrive at the conclusion that there has been an increase in geographic sorting. Not only has there been a steady and consistent rise in spatial sorting along political dimensions since 1970, but it has also rapidly increased at an increasing rate since approximately 2000.

Their results, while robust and significant, do not account for something that changes how we view the assumptions of Tiebout's hypothesis: that migration is costless. Their panel ends in 2016, whereas the COVID-19 pandemic didn't manifest until 2020. Why is the omission of the pandemic years significant? Because it allows us to study Tiebout's hypothesis in a setting that addresses the most pervasive criticism of his assumptions, that of zero mobility costs. As I will discuss in the next section, and briefly discussed earlier, the pandemic, coupled with the advent of Work From Home (WFH), caused migration costs to asymptote to zero[2]

Famously, Truman Bewley roundly criticized Tiebout's hypothesis in a 1981 article. Chief among his complaints was that Tiebout's, roughly, 9 assumptions are too restrictive (Bewley 1981). While restrictive assumptions are integral to economics, especially for an issue as intractable as preference-based sorting, some of the ones Tiebout made were glar-

[2] I discuss a formal definition of mobility costs in 3.1 that differentiates between movement and employment costs.

ing. The most significant of these was that there were no costs associated with moving. When in reality, mobility costs can be prohibitive for many people. Acknowledged as the most restrictive and necessary assumption, this is also the hardest to modify; up until the COVID-19 pandemic, it was nearly impossible to observe costless migration.

Rhode and Strumpf's 2002 "Assessing the Importance of Tiebout Sorting: Local Heterogeneity from 1850 to 1990" made significant strides in tackling the notion of mobility costs by studying Tiebout's hypothesis in a world of declining mobility costs. Their model and results show that as mobility costs decrease, sorting increases, as does the heterogeneity in residents' preferences across jurisdictions. Their paper falls short in that their empirical results, while significant and robust, are dated. They show that for the late 19th and 20th centuries, there has been an increase in sorting along many dimensions across jurisdictions. Their results form a clear precursor to those of Kaplan et. al.

This paper seeks to make a contribution by unifying and extending the contributions of both Rhode and Strumpf and Kaplan et. al. Presenting a unified model that addresses Tiebout sorting under low mobility costs and preferences over politics is a novel contribution to the literature. The empirical results of analyzing sorting during COVID-19 is a first-of-its-kind analysis and presents more novel results that extend the body of work started by Tiebout and continued by Rhode and Strumpf, and Kaplan. et. al.

3 The Model

3.1 WFH and Mobility Costs

The central aspect of Tiebout's 1956 hypothesis is the assumption that mobility costs are zero. This assumption, while unrealistic and restrictive, was necessary to make the issue of geographic sorting and spatial equilibrium tractable. Since then, there have been many modifications and applications of the model's framework (see Rosen and Roback's classic articles as well as work by Glaeser). However, none of these made any real progress in dealing with mobility costs to make their models simultaneously more applicable and tractable.

In 2002, Rhode and Strumpf formalized Tiebout's model and added mobility costs. Their results were novel and corroborated with data, and their iteration allowed for theoretical work on migration and spatial equilibrium to become more tractable.

The idea of work-from-home provides a natural way to observe costless migration, in a sense. While there will never be anyway to observe a large number of observations who move at literally no cost, re-framing the definition of mobility costs in terms of employment allows for this analysis to make use of both the original Tiebout model and Rhode and Strumpf's mobility cost modified model.

Definition 3.1 (Mobility Costs)**.** *Mobility Costs are understood to be the costs of moving-related* *to employment. They are understood to be foregone wages, the costs of searching for a new job, and the potential for a reduced salary.*

I incorporate this definition of mobility costs as follows. I assume that it is initially costless to locate. In a sequential environment, choosing where to initially live, called the pre-WFH equilibrium, has no mobility cost at all. I then posit that the only cost to migration from the initial location is those that are related to employment: foregone wages, the search costs, and the potential for a lower salary in the new locale. Under these assumptions, I am able to claim that the initial location decision has no mobility costs and that under WFH, there are no mobility costs associated with any proceeding location decisions.

This assertion allows me to do two things with this analysis that follow closely to each of the modified models. It allows me to use the framework from Brueckner et. al. that assumes costless migration to arrive at concrete results. It also allows us to use a modified version of Rhode and Strumpf's model to explain and contextualize these results with political sorting while illustrating how WFH induces costless migration.

3.2 Set-up

This section borrows liberally from Brueckner et. al., their notation is retained in its near entirety.

This intercity model has two cities, denoted by $j = \{1, 2\}$, with equal land areas, hence zero land supply elasticities, that accommodate a fixed total population of $2\overline{N}$. Define the wage in city j as $w(L_j, \alpha_j)$, where L_j is the labor force in city j, and α_j is the productivity endowment. The wage then has the following properties: $\frac{\partial w}{\partial L} < 0$ and $\frac{\partial w}{\partial \alpha} > 0$.[3]

Without work from home (WFH), the population of a city must equal its labor force, so the wage without WFH is given by $w(N_j, \alpha_j)$. It is the case that city 1 and 2 differ in their productivity α_j and their amenities A_j with city 1 being more productive and more heavily amenitied, $(A_1 \geq A_2)$ and $(\alpha_1 \geq \alpha_2)$. The cities also differ in their degree of political heterogeneity $G(N_j)$ (carelessly called heterogeneity in this paper), where a greater value of G is associated with more heterogeneity.[4] Heterogeneity in this situation means a larger political minority. If a city is very politically homogeneous, that means more people share a political affiliation or occupy the same location in the policy space. So an increase in political heterogeneity means an increase in those residents who are in the political minority, or equivalently the political minority becomes more powerful. The initial ordering of G_j^* is arbitrary and indeterminate.

[3] This first property is because the wage function, in this case, is the downward-sloping inverse demand curve for labor.

[4] It is important to discern that the heterogeneity term only says that city 1 is more or less different in the political opinions of its population than city 2. It says nothing of which city is more left or right wing.

Consumers, or citizens or residents, regardless of type, have identical preferences given by the quasi-linear and singleton-separable utility function u(A_j, e_j, N_j, q_j)= $A_j + e_j + v(q_j) - G(N_j)$, where q_j is units of housing consumption and e_j is units of composite non-housing consumption. The units of measurement for amenities and composite consumption are chosen such that their linear utility coefficients are the same and equal to unity. Importantly, as utility is quasi-linear, then each of the non-linear terms is increasing in N_j; this leads to the pivotal fact for this analysis that heterogeneity increases with population.[5]

Allowing the price of housing to be denoted by p_j, the consumer's budget constraint becomes $e_j = w(N_j, \alpha_j) - p_j q_j$ which assumes the price of non-housing consumption is the same across cities and equal to unity. Applying Lagrangian relaxation allows the utility function to be rewritten as $u_j = A_j + w(N_j, \alpha_j) + v(q_j) - p_j q_j - G(N_j)$. The third and fourth terms express "net housing utility" and can be expressed as $H(N_j)$, which is decreasing in N_j for all j.[6] Then,

$$u_j = A_j + w(N_j, \alpha_j) + H(N_j) - G(N_j), \quad j = \{1, 2\}. \tag{1}$$

In the absence of WFH, the equilibrium condition is the consumer utility function in (1) is equalized between locations via costless migration .

Definition 3.2. *The pre-WFH equilibrium is given by*

$$A_1 + w(N_1^*, \alpha_1) + H(N_1^*) - G(N_1^*) = A_2 + w(N_2^*, \alpha_2) + H(N_2^*) - G(N_2^*) \tag{2}$$

where * denotes pre-WFH.

The immediate implication from (2) is $N_1^* > N_2^*$. See Appendix 1 for proof.

Given that city 1 is larger than city 2, its housing price is higher than city 2's ($p_1^* > p_2^*$).

Now suppose that WFH becomes a feasible option.

Since that means an individual can work in either city, regardless of their residence, equilibrium requires them to be indifferent between either work location. This implies an equalization of wages, $w(\tilde{L_1}, \alpha_1) = w(\tilde{L_2}, \alpha_2)$, where $\tilde{L_j}$ is the post-WFH employment level in city j.[7] Wage will then drop out of the equilibrium condition. An immediate consequence

[5] Taken from Rubinstein

[6] This effect is due to the positive relationship between population and housing prices, shown in the following derivation. As land-area of a city is normalized to 1 we get $q_j = \frac{1}{N_j}$. This implies that the FOC wrt housing is ($v'(q_j) = p_j$) which yields $H(N_j) = v(q_j) - p_j q_j = v(\frac{1}{N_j}) - v'(\frac{1}{N_j})(\frac{1}{N_j})$ which it is easy to see is decreasing in N_j. To verify this notice that differentiating $H(N_j)$ yields $H'(N_j) = (\frac{1}{N_j^3}) v''(\frac{1}{N_j}) < 0$. Which is an expression proportional to minus the modulus of $\frac{d}{dN_j}(p_j = v'(\frac{1}{N_j}))$.

[7] I assume that residential relocation leaves worker productivity unaffected.

of this is that under WFH, population and employment levels need not be equal.

Definition 3.3. *The WFH equilibrium is given by*

$$A_1 + H(\tilde{N}_1) - G(\tilde{N}_1) = A_2 + H(\tilde{N}_2) - G(\tilde{N}_2) \tag{3}$$

where $\tilde{N}_j$ is the WFH population of city j.

With city 1 being more amenitied and more productive, it is again necessarily the case that $\tilde{N}_1 > \tilde{N}_2$ to equate both sides of (3).[8] This reveals again $\tilde{p_1} > \tilde{p_2}$, which cancels the amenity advantage of city 1.

Before we can compare equilibria and gather results about political sorting, we must understand how these equilibria are realized. This is done so below using a redefinition of the utility function and a model similar to that present in Rhode and Strumpf.

3.3 Explaining and Contextualizing the Results

The above results gathered from Brueckner et. al.'s framework are important; however, we are yet unable to make a definitive statement about political sorting in the Tiebout framework using those results. To make a claim about if there does, in fact, exist political sorting under WFH, we turn our attention to yet another model modification. This time following from Rhode and Strumpf, 2002 where we again borrow from their model. I retain less of their original notation, instead modifying it to fit into the existing framework and notation from Brueckner et. al. when appropriate.

Their model modifies, and formalizes, Tiebout's classic hypothesis by adding mobility costs, and arrives at the novel conclusion that, under certain assumptions, as mobility costs approach zero, Tiebout sorting will increase and heterogeneity *across* communities increases. I reformulate their model in our existing framework, relax one of their assumptions, and arrive at a more general conclusion regarding political sorting using the arrived to results from Brueckner[9].

The population remains fixed at $2\bar{N}$, and the citizens remain indexed by i. Let C_i be the city containing citizen i and call $\mathcal{A} = (C_1, C_2, ..., C_{2\bar{N}})$ the allocation of individuals across cities[10].

[8]This follows from the same argument as the proof of the implication of (2).

[9]Explicitly, I relax their assumption of quadratic preferences and prove the conclusions in a more general sense, ignorant of the functional form of the re-realized utility function.

[10]Importantly, this generalized model applies to any finitely large number of cities, not just the two city case previously.

Importantly still, we can and must re-represent the utility function. In (1), utility was presented in the singleton-separable, quasi-linear form with amenities, productivity, and population as arguments. Each city j then had its own unique combination of amenity level, population, and productivity endowment. Through some local political action that is identical across cities, either voting or agenda setting by the city council, local policies are enacted. These policies are determined from the combinations of amenities, wages, productivity, etc., in a manner such that the utility function defined in (1) is equivalent to one defined over a vector of local policies.

An intuitive way of understanding this is that a city is endowed with amenities, population, wage, housing utility, and heterogeneity, which in turn determines the individual-level city-specific utility function. Each city, in turn, has a local government, that sets policies: this can be done either via popularly voting for referenda and ballot initiatives or politicians who, in turn, enact policies to maximize their chances for reelection. These policies will be responsive to the population, amenities, and productivity of the city. In other words, the policies are shaped by, and targeted towards, those who live in the city and the characteristics of the city. These policies allow for people to *directly* realize amenities, productivity, and population in their utility function [11]

In turn, this means that the individual can realize the utility of the same city in two identical ways: the separable and quasi-linear (1) or the vector-argument form presented below. The discerning economist will realize that as utility is ordinal, our particular utility function has an identical co-domain, or ranking, over the choice set of policies as it does over the set of population, amenities, and productivity. Using this, we can introduce type dependent utility function to arrive at political sorting.

For each city j, have the vector of policies for the city be $\mathbf{P}_j \in \Gamma$, where $\Gamma \subseteq \mathbb{R}^n$ is compact. Intuitively think of $\mathbf{P}_j$ as the n-tuple corresponding to the n *realizable* policies of city j where each can be either real-valued (taxation or spending) or unordered and categorical (school curriculum) [12]. Call $\mathcal{P} = (\mathbf{P_1}, \mathbf{P_2}, ..., \mathbf{P_j})$ the set of city policies.

Before proceeding, it is helpful to step back and see what has been done. The above setup has modified the Tiebout hypothesis to extend to not only public goods of a collection of cities but the policy agenda as well. This is done by realizing that an individual with preferences over the choice set composed of population, wage, amenities, etc., will also have preferences over policies that are determined by population, wage, amenities, etc. So, making use of the ordinal property of utility, we have redefined the choice set to be over policies, not characteristics, and as the characteristics determine the policies, we arrive at

[11]Instead of deriving utility from living in a productive and amenitied city with a large population, the individual can equivalently derive utility from the policies of the city that allow them to use and benefit from the amenities, productivity, and population.

[12]I further impose that there is a bound on the returns to scale of public good spending, subsidies, and other policies that can be targeted towards subgroups to rule out exceptionally large and heterogeneous communities.

equivalent utility functions. $u(A_j, \alpha_j, N_j) \equiv u(\mathbf{P_j})$.

We further assume that each citizen has a type $\theta_i \in \Theta$, where Θ is finite, compact, and ordered[13]. The type is realized via the utility function $u(\mathbf{P_j}|\theta)$, and $\mathbf{P}_\theta \in \Gamma$ is the idea policy vector for type θ. Further, presume that $|\Theta| \leq 2\bar{N}$. This is a formal way of saying that each of the $2\bar{N}$ citizens prefers a certain local policy agenda (or equivalently, a certain combination of amenities, productivity, and population). In the framework presented in the prior section, there are 2 types, those who prefer city 1 and those who prefer city 2[14].

The results below rely heavily on the following assumption and definitions [15]:

Assumption 3.4 (Single-Peaked Preferences). $\mathbf{P_j} \in \Gamma$ *and* $u(\mathbf{P_j})$ *is twice differentiable and concave in* $\mathbf{P_j}$ *where* $u''(\mathbf{P_j}|\theta) < 0$ *and* $u'(\mathbf{P_j}|\theta) > 0$ *for* $\mathbf{P_j} < \mathbf{P}_\theta$*; and* $u'(\mathbf{P_j}|\theta) < 0$ *for* $\mathbf{P_j} > \mathbf{P}_\theta$ *and* $u'(\mathbf{P}_\theta|\theta) = 0$

Definition 3.5 (Social Welfare). *The aggregate measure of social welfare for any allocation* $\mathcal{A}$ *and set* $\mathcal{P}$ *is the sum of each citizen's utility:*

$$W = \sum_i \sum_j u(\mathbf{P_j}|\theta_i) \tag{4}$$

Importantly, the functional form of the utility function is unimportant.

Definition 3.6 (City Decisions). *Each city chooses a vector of policies* $\mathbf{P_j^*}$ *to maximize the sum of the utility of its current residents* [16]*:*

$$\mathbf{P_j^*} = \underset{\mathbf{P_j} \in \Gamma}{argmax} \sum_i u(\mathbf{P_j}|\theta_\mathbf{i}) \tag{5}$$

Because of Assumption 3.10, we know that $\mathbf{P_j^*}$ *exists. For clarity, there are some situations where* $\mathbf{P_j^*} \in \emptyset$*. An important support for these two definitions is that the functional forms of utility are unimportant, and I arrive at the same results regardless; however, (4) and (5) will have parallel functional forms.*

Assume the individuals move in any finite order that can be either deterministic or stochastic, which is called citizen *i's* location decision event. When the event occurs citizen i can change cities at the cost of m_i utils, which is individual specific and identical across

[13]This simply means that all i individuals identify with some type, and that type can be ordered based on some metric. It will be helpful to think of "scope of government" as the metric so then we are endowed with order $\geq$ which orders the types from preferring the largest scope of government to the smallest.

[14]This can be extended to the differential case, and it would not be incorrect to say that there are those who prefer city 1 in the amenity and productivity differential case, those who prefer city 2 in both, and those who prefer city 1 in one differential and city 2 in the other.

[15]Here is where I relax the assumption of quadratic preferences present in Rhode and Strumpf and arrive at a more general conclusion that holds for an arbitrary and general functional form of $u(\mathbf{P_j})$

[16]This is a leading case and is identical to a world with a majoritarian rule, side payments, and transferable utility. For an exposition on how side payments and transferable utility induce efficiency, see Buchanan and Tullock 1962.

cities.

Assume that movements are myopic in that agent i takes the prevailing $\mathcal{P}$ as given and only considers moving to the city that maximizes their type-conditional utility. This move is ignorant of how it will affect $\mathcal{P}$ or other people's movement decisions. An empty city sets its policy vector equal to the incoming citizen's ideal.

Definition 3.7 (Myopic Move). *Under the myopic movement rule, individual* i *of type θ_i moves from city 1 to city 2 at their location decision event iff*

$$\mathbf{P}_2^* = \underset{\mathbf{P}_2 \in \mathcal{P}}{argmax}\ u(\mathbf{P_j}|\theta_\mathbf{i}) \tag{6}$$

and

$$u(\mathbf{P}_2^*|\theta_i) > u(\mathbf{P}_1^*|\theta_i) + m_i \tag{7}$$

In equilibrium, no citizens will move unless subject to some random shock.

Definition 3.8 (Equilibrium). *An equilibrium is an allocation $\mathcal{A}$ of individuals such that no individual moves allocations given m_i*

This result is in line with that from Tiebout's original model: when the number of cities is at least as large as the number of types, then individuals will sort themselves based on type into homogeneous communities providing their ideal **P**. It is easy to see the following proposition.

Proposition 3.9. *If $2\bar{N} \geq |\Theta|$ and policies are set via (5), then W is maximized when each city contains only one type* [17].

While it is difficult to appropriately measure the degree of heterogeneity, it is an important and clear point that social welfare is positively related to increased sorting, or equivalently, lower within community heterogeneity and higher across community heterogeneity in the Tiebout model.

Again, assuming single-peaked preferences and policies set via (5) is sufficient to show that sorting is a self-enforcing, increasing returns process. The movement of an individual of type θ_a increases the attractiveness of the receiving community and reduces the attractiveness of the sending community for all other type θ_a citizens. This has the opposite effect for other types as fewer type θ_a people make the city more attractive for θ_a^c types.

[17] This proposition corroborates the claim made in the previous section that heterogeneity in policy preferences has a negative relationship with utility (and by extension, welfare) in the Tiebout model.

To avoid the complexity shown in Kollman et. al. 1997, I assume only myopic movement and ignore the cascading effects of if the individual considered the general equilibrium implications of their decision. In a large population, a single individual has an ϵ-negligible effect on policy.

Prop. 3.15 shows that any myopic move has a strictly positive effect on social welfare, and, as mobility costs fall, there is increased sorting. We can then say that WFH sees an increase in social welfare.

Proposition 3.10. *When individual moves obey (6) and (7) and policies are set via (16), then:*

a) Any individual move strictly increases W and does so by more than m_i

b) If m_i falls, then resident i *will either stay in the originating city or move. If they move, then W will increase. The movement process will yield a new equilibrium with a higher W. More explicit to WFH this is* $\sum_i \sum_j [A_j + w(N_j^*, \alpha_j) + H(N_j^*) - G(N_j^*)|\theta_i] < \sum_i \sum_j [A_j + w(\tilde{N}_j, \alpha_j) + H(\tilde{N}_j) - G(\tilde{N}_j)|\theta_i]$

Proof 3.11. *See Appendix 1*

Three comments follow from this proposition:

1. Proposition 3.10 holds in the case of a Leviathan government where $\mathcal{P}$ is fixed, here (6) and (7) imply (21) is positive.
2. More generally, this result holds if the social welfare function (4) weakly reflects individual preferences and each community maximizes residents' welfare, as measured by the social welfare function
3. Failure of the myopic movement rule allows for the consideration of externalities. In other words, the myopic movement rule requires that (21) be positive. Suppose instead that citizens are forward-looking and move if (21)+(22) is positive. If (21) is negative, then (19)+(20)+(21)+(22) could be negative, and the proposition fails and welfare falls. This allows for forming the framework to analyze externalities.

The issue of interest is how a reduction in mobility costs can affect the distribution of policy outcomes.

Proposition 3.12. *Under Assumption 3.4, when $|\Theta| = 2 = C$, individual moves that satisfy (6) and (7) lead to an increased variation of policy outcomes across cities.*

Proof 3.13. *See Appendix 1*

In this case, the city's policies will be the weighted average of the two type's ideal policies, where the weight of the type's preferences depends positively on its population share.

Clearly, any myopic move will widen the difference in policy between two cities by pushing the policy in the receiving(sending) city toward(away from) the mover's ideal.

The results of this section are crucial to determining the existence of political sorting. By understanding the behavior of belief heterogeneity on the level of individual movement decisions, we can introduce that term into our modification of Brueckner et. al.'s model. By doing so, we can arrive at a definitive and empirically testable result regarding the existence of political sorting under work-from-home.

3.4 Comparing Equilibria

To compare the pre-WFH and WFH equilibria, rewrite (2) and (3) as

$$A_1 - A_2 + H(N_1^*) - H(N_2^*) - G(N_1^*) + G(N_2^*) = w(N_2^*, \alpha_2) - w(N_1^*, \alpha_1) \quad (pre - WFH) \tag{8}$$

$$A_1 - A_2 + H(\tilde{N}_1) - H(\tilde{N}_2) - G(\tilde{N}_1) + G(\tilde{N}_2) = 0 \quad (WFH) \tag{9}$$

Comparing (4) and (5) leads to the following propositions

Proposition 3.14.

$$\tilde{N}_1 > (<) N_1^* \;\; as \;\; w(N_2^*, \alpha_2) > (<) w(N_1^*, \alpha_1) \tag{10}$$

Proof 3.15. *See Appendix 1*

It is, however, impossible to arrive at a direct comparison of $\tilde{N}_1$ and N_1^* using (6) due to city 1 having a dual advantage over city 2. In other words: $sign(w(N_2^*, \alpha_2) - w(N_1^*, \alpha_1))$ is ambiguous. This analysis arrives at definitive conclusions by considering one advantage at a time. The rest of this analysis always assumes that city 1 has the advantage over city 2.

3.4.1 Productivity Differential

Suppose A_1=A_2, $\alpha_1 > \alpha_2$. Then (4) shows that $w(N_2^*, \alpha_2) < w(N_1^*, \alpha_1)$ and $p_1^* > p_2^*$. To see this recognize that (4) becomes $H(N_1^*) - H(N_2^*) - G(N_1^*) + G(N_2^*) = w(N_2^*, \alpha_2) - w(N_1^*, \alpha_1)$. Since $N_1^* > N_2^*$ holds from above, we have that the LHS of (4) is negative because $H_N < 0$ and $G_N > 0$; this means RHS of (4) is also negative, so $w(N_2^*, \alpha_2) < w(N_1^*, \alpha_1)$.

From (6), this implies $N_1^* > \tilde{N}_1$ or that city 1's population falls while that of city 2 rises.[18]

Since A_1=A_2, (5) necessarily implies that $H(\tilde{N}_1) = H(\tilde{N}_2)$ and $G(\tilde{N}_1) = G(\tilde{N}_2)$ then we see that the population changes end up equating the populations, $\tilde{N}_1 = \tilde{N}_2 = \overline{N}$. Equal

[18] Since the land area is fixed, this assumes away the construction boom phenomenon discussed in Howard 2020.

populations, in turn, imply equal housing prices, $p_1^* > \tilde{p_1} = \tilde{p_2} > p_2^*$. Citizens earning the same wage and paying the same prices ensure equalized utilities. The movement of people from city 1 to city 2 shows that $G(N_1^*) > G(\tilde{N}_1)$ and $G(N_2^*) < G(\tilde{N}_2)$, or the movement of people from city 1 to city 2 made city 1 more politically homogeneous (less heterogeneous) and city 2 more heterogeneous.

WFH breaks the employment-population link and allows employment and population to differ as people continue to work in City 1 while relocating to City 2. Formally this means $\tilde{L_1} > N_1^*$ and $\tilde{L_2} < N_2^*$ both hold, signifying that employment rises in City 1 above its falling population and falls in City 2 below its new rising population.[19] The drop in employment in City 2 means that some original residents of City 2 find new work in remote jobs in City 1.

The above can be summarized as follows:

Claim 3.16. *When City 1 has only a productivity advantage over City 2, some residents move to City 2 under WFH and retain their jobs in City 1. Then City 1's population and housing prices fall while they rise in City 2. Employment in city 1 rises above its lower new population while the new larger population in city 2 eclipses its falling employment. Given its larger initial population, city 1 is more politically heterogeneous than City 2. City 1 sees a decrease in its heterogeneity (it becomes more homogeneous), and City 2 sees an increase in its heterogeneity.*

This can be represented by the following inequalities:

$$\tilde{L_1} > N_1^* > \tilde{N}_1 = \overline{N} = \tilde{N}_2 > N_2^* > \tilde{L_2} \tag{11}$$

$$w(N_1^*, \alpha_1) > w(\tilde{L_1}, \alpha_1) = w(\tilde{L_2}, \alpha_2) > w(N_2^*, \alpha_2) \tag{12}$$

$$p_1^* > \tilde{p_1} = \tilde{p_2} > p_2^* \tag{13}$$

$$G(N_1^*) > G(\tilde{N}_1) \;\; and \;\; G(N_2^*) < G(\tilde{N}_2) \;\; and \;\; G(\tilde{N}_1) = G(\tilde{N}_2) \tag{14}$$

3.4.2 Amenity Differential

Suppose $A_1 > A_2, \alpha_1 = \alpha_2 = \overline{\alpha}$. Since $N_1^* > N_2^*$ and $w_N < 0$ we have that $w(N_2^*, \overline{\alpha}) > w(N_1^*, \overline{\alpha})$. By (6) we have that $\tilde{N}_1 > N_1^*$. This extends to show $\tilde{N}_1 > \tilde{N}_2$. With $A_1 > A_2$, (5) necessarily implies $H(\tilde{N}_1) < H(\tilde{N}_2)$ and $G(\tilde{N}_1) > G(\tilde{N}_2)$

To see this, we notice an increase in the population of City 1 and a corresponding fall in City 2. This will end up exacerbating the intercity price and heterogeneity differentials.

[19] To loosely prove this claim I show that $N_1^* > \tilde{L_1}$ and $N_2^* > \tilde{L_2}$ cannot both hold, nor can the reverse. Either set of inequalities violates the requirement that the city populations before WFH or the employment after WFH individually sum to $2N$. So, it must always hold that in the differential productivity case, $N_1 < \tilde{L_1}, N_2^* > \tilde{L_2}$ or $N_1 > \tilde{L_1}, N_2^* < \tilde{L_2}$.

With the population increasing in City 1, we have that $\tilde{p_1} > p_1^*$ and $p_2^* > \tilde{p_2}$ in City 2. This population trend also leads to an increase in the heterogeneity of City 1 and a decrease in the heterogeneity of City 2.

People leaving City 2 for City 1 retain their original jobs leading to employment eclipsing the population in City 2 and the reverse in City 1. To convince yourself of this, recall that WFH requires $w(\tilde{L_1}, \overline{\alpha}) = w(\tilde{L_2}, \overline{\alpha})$, which under the equal productivity assumption requires $\tilde{L_1} = \tilde{L_2} = \overline{N}$. Since $\tilde{N}_1 > \tilde{N}_2$, then it follows that $\tilde{N}_1 > \tilde{L_1} = \overline{N} = \tilde{L_2} > \tilde{N}_2$.

Correspondingly, we see that $\tilde{L_1} < N_1^*$ and $\tilde{L_2} > N_2^*$ as employment falls in city 1, but the population rises, and the reverse occurs in city 2. The preceding inequalities follow because $N_1^* > \overline{N} = \tilde{L_1}$ and $\tilde{L_2} = \overline{N} > N_2^*$. The drop in employment in city 1 means many people who originally live in city 1 work remotely in city 2.

The above can be summarized as:

Claim 3.17. *When City 1 has an amenity advantage, residents move from City 2 to City 1 under WFH and retain their jobs in City 2. Population and housing prices then rise in City 1 and fall in City 2. Despite its rising population, employment falls in City 1 and rises in City 2, eclipsing its falling population. Before WFH, City 1 had higher housing prices and lower wages than City 2. This is the standard result of the Roback-Rosen model, where cities differ only in amenities. The wage and housing price differences worked to offset the amenity advantage of City 1; however, when wages are equalized across cities, a larger price differential is required to equalize utilities, resulting in an increase in housing prices for City 1 and a decrease in City 2. Due to the positive relationship between population and heterogeneity, the more amenitied city becomes more politically heterogeneous, and the less amenitied place becomes more politically homogeneous.*

This can be represented by the following inequalities:

$$\tilde{N}_1 > N_1^* > \tilde{L_1} = \overline{N} = \tilde{L_2} > N_2^* > \tilde{N}_2 \tag{15}$$

$$w(\tilde{L_1}, \alpha_1) < w(N_1^*, \alpha_1) < w(N_2^*, \alpha_2) < w(\tilde{N}_2, \alpha_2) \tag{16}$$

$$\tilde{p_1} > p_1^* > p_2^* > \tilde{p_2} \tag{17}$$

$$G(\tilde{N}_1) > G(N_1^*) \;\; and \;\; G(\tilde{N}_2) < G(N_2^*) \;\; and \;\; G(\tilde{N}_1) > G(\tilde{N}_2) \tag{18}$$

3.5 Results and Implications of the Model

The above section provides two different settings to see how city heterogeneity changes under WFH: one in which there is a productivity differential between the cities, the other when there is an amenity differential. By presenting the results of this model on the political heterogeneity of cities I can then interpret them in terms of political sorting using the model framework put forth by Rhode and Strumpf.

The above section provides the following results:

Results 3.18.

<u>Result 1:</u> *Political heterogeneity within a city and the city's population have a positive relationship. Utility decreases with population.*

<u>Result 2:</u> *In the case of differential advantages, productivity or amenities, the more advantaged city will be more politically heterogeneous pre-WFH.*

<u>Result 3a:</u> *In the case of a productivity differential, under WFH, there is a convergence in, or elimination of, the intercity population, wage, price, and heterogeneity differentials. The more productive city sees a lower population, higher employment, lower wage, and lower home price, and it becomes more politically homogeneous. The less productive place sees an increased population, wage, home price, and heterogeneity along with lower employment.*

In the case of an amenity advantage, the opposite effect is observed under WFH where the differentials are exacerbated. The more amenitied place sees its population rise, employment fall, wages fall, prices rise, and heterogeneity rise. The opposite effect happens in the less amenitied city.

<u>Result 3b:</u> *Productivity differential:* $G(N_1^*) > G(\tilde{N}_1) = G(\tilde{N}_2) > G(N_2^*)$
Amenity Differential: $G(\tilde{N}_1) > G(N_1^*) > G(N_2^*) > G(\tilde{N}_2)$

<u>Result 3c:</u> *A productivity advantage will decrease a city's political heterogeneity under WFH, but an amenity advantage will increase it.*

<u>Result 3d:</u> *In the case of an amenity differential, across-city political heterogeneity is exacerbated; whereas, in the case of a productivity differential, it is eliminated.*

Putting this analysis together with the foundational work following from modifying Brueckner, we can arrive at the following definite result:

Results 3.19. *In the case of a productivity differential, there is no theoretical evidence of political sorting in the Tiebout framework. In the case of an amenity differential, there is evidence of political Tiebout sorting. These are shown by comparing the pre-WFH and WFH heterogeneity relations with the contextualization provided by the Rhode and Strumpf analysis. More specifically, political sorting is consistent with myopic movement and increases across community heterogeneity. As there is an equalization between cities in the productivity differential case, this is evidence against political sorting As there is an increase in heterogeneity between cities in the amenity differential case, I prove that there is evidence of political sorting in this differential case.*

These results are clearer by noticing that the Brueckner framework is identical to Theorem 5.9. We then see that if there is decreased political variation (lower heterogeneity) across cities, then moves fail to satisfy (17) and (18), thus are not political Tiebout moves [20].

4 Data

For this thesis, I make use of a novel and self-constructed data set. For my units of observation, I use Combined Statistical Areas (CSA); which are defined by the Office of Management and Budget as "consisting of various combinations of adjacent metropolitan and micropolitan areas with economic ties measured by commuting patterns".

I make use of 6 existing data sets that I clean and merge into the data set used for the econometric analysis. The first data set is that of the Redfin Migration Report, which reports a sample of 2 million users who searched on Redfin.com for a home across 100 major metropolitan areas by quarter, and ultimately purchased a home and relocated (CITATION).

The data from Redfin is given on the CSA level and provides many variables of interest. For this analysis, I made use of the variable that measured the percentage of people at a given origin who moved to a destination in a given quarter.

It was necessary to clean the data to get it into the appropriate format. I restricted the number of CSAs to those where all the destinations were also origins. This was to accomplish a closed system of origin-destination pairs.

The second data set that I used was county-level presidential election data from MIT Election Lab (CITATION). This data set provided county-level presidential election returns for every presidential election from 2004 to 2020. I restricted the sample to those presidential elections that roughly coincide with the dates of my panel: 2016 and 2020. The logic of choosing the presidential election is that everyone is faced with the same ballot and eliminates the effect of idiosyncratic race characteristics like a candidate being unopposed or a candidate dying close to election day.

After restricting the dates, I sought to create the political variable of interest. This is defined as the modulus of the difference in the average Democrat vote share between 2016 and 2020 in the origin and the average Democrat vote share between 2016 and 2020 in the destination. To accomplish this, I took the number of votes received by the Democrat in either election, in this case, Hillary Clinton or Joe Biden, and divided it by the number of total votes cast. For the 2020 presidential election, I had to deal with the different modes of voting allowed for by the pandemic. To that end, for each county, I summed the total number of votes received by Democrats across election, provisional, and early voting, and

[20] We cannot have the failure of $|\Theta| = 2 = C$ to compare equilibria or outcomes.

divided it by the total number of votes cast.

The task was then to merge the two data sets. To do this, I merged the CSA-level migration data with a data set that listed the population of all counties in each CSA, including county FIPS numbers. I then merged that data set with the county-level election data by county FIPS.

The task at hand now was to generate a workable iteration of the Democrat vote share variable for each origin and destination CSA. To accomplish this, I first took the average of the county-level 2016 and 2020 Democrat vote share variables in each CSA, weighted by county population. Then with the average Democrat vote share for each year in each CSA, I took the average of the two-year averages. In essence, this vote share variable is an average over two elections of a population-weighted average of two election year's votes for each county in a CSA. This data set is now referred to as the master. See Appendix 2, Table 1 for a list of CSAs, Table 2 for a list of states covered in the panel, and Table 3 for dates of the panel. I provide density plots of the Democrat vote share for 2016 and 2020 for both origin and destination CSAs as well as densities of the overall Democrat average vote in the origin and destination CSAs and the overall distribution of Democrat vote share in 2016 and 2020. These are Figures 1-4 in Appendix 2. Figure 5 in Appendix 2 shows the time series plot of the mean of the difference in average Democrat vote share between origins and destinations variable at each quarter of the panel.

The only aspect that remained was to merge the existing data set with those containing latitude and longitude data, wage, home price, race, and industry information.

Each of these was a straightforward procedure. I generated an origin ID and destination ID that was unique for each CSA in either category. I then downloaded data sets from Census Reporter or Home Area containing the variables of interest (CITATION). Each time entailed downloading the data set, dropping superfluous variables, and merging the data set with the master data set using the unique origin and destination IDs which were easily replicated in the new data sets.

Upon complete merging, I defined the variables of need, namely the physical distance between the origin and destination, racial distance, industrial distance, and if the origin and destination lie in the same state for each origin-destination pair. I formal definitions of the variables in Section 5. To calculate the physical distance between the origin and destination, I utilized Stata's geodist feature.

Needed for the modifications of the baseline model were wage, income, and home price data. I used the same sources as above to get the needed data for each origin and destination CSA and merged them with the master data set using the same procedure.

The final version of the data set consisted of 17,865 observations of 1,821 unique origin-destination CSA pairs over 21 quarters ranging from the first quarter of 2017 to the first quarter of 2022. The data encompasses 76 total CSAs across 31 states, with 76 origin CSAs and 73 destination CSAs. See Table 5 for summary statistics of the final data set.

Though the Redfin and election data sets cover CSAs and counties in all fifty states, there were some inconsistencies that prevented this panel from covering all 50 states and 172 CSAs. The inconsistencies in the name of some CSA between Redfin and OMB lead to those who did not have the same name being thrown out. Several states, namely California and Wyoming, had inconsistencies in their election data. The figures reported in the MIT election lab county-level data were different than those reported by the respective secretaries of state. Due to these inconsistencies, I opted to err on the side of caution and throw out CSAs not matching the OMB name and those states with electoral inconsistencies.

5 Empirical Analysis

Given the robust data set available, I am able to test several hypotheses about politically motivated movements in the US. The benefit of the universal nature of the COVID-19 pandemic is that every location in the US was hit at approximately the same time. Moreover, each city and state in the US followed roughly the same schedule regarding restrictions and lockdowns. This mirrored national recommendations of stay-at-home orders and mask mandates.

Where the treatment variable of COVID-19 varies is that regulations varied state by state. While the nation as a whole was under a national emergency for COVID-19, some states reopened schools and lifted capacity caps for restaurants while other states kept outdoor mask mandates and social distancing regulations in place far into the end of the year. The coincidence of the 2020 presidential election falling in the middle of the pandemic leads to some more variation resulting from COVID-19. Some states embraced ease-of-voting measures like universal mail-in ballots and no-excuse absentee voting while others were reticent to expand the franchise and only allowed expanded early voting due to it being a national emergency.

The COVID-19 pandemic thus leads to some variation in observable policies on the local and state level. Everyone in the country was affected by the pandemic, yet they experienced it differently based on where they lived. This difference likely motivated people to exploit work-from-home and move.

This framework mimics very closely a natural experiment. Moreover, I am faced with an identical and time-invariant treatment that affects all groups uniformly. This allows me to make use of variation across the groups and compare outcomes between groups using

COVID-19 as a treatment. I discuss this more in section 5.4.

Specifically, the question that I am aiming to answer in this empirical section is, "Does there exist evidence of political Tiebout sorting in the presence of an amenity differential and not in the case of a productivity differential." To begin, I posit a baseline linear model and estimates. From there, I proceed with two modifications, making use of the linear model framework and exploiting three-way fixed effects and triple interactions.

The first modification interacts with the variable of interest, the average Democrat vote difference between origin and destination, with a categorical variable for quarters in the panel. The second interacts with the same variable of interest with the group and the COVID treatment variable.

5.1 Baseline Model

The goal of this section is to arrive at a model that provides a causal estimate of the following conditional expectation:

$$\mathbb{E}[\text{share of people moving from i to j}|\text{origin, destination, quarter,}$$

$$\text{difference of average Democratic vote share between 2016 and 2020 for the origin and the destination,}$$

$$\text{ethnic distance between origin and destination, industrial distance between origin and destination}$$

$$\text{dem vote difference between origin and destination over time, physical distance between origin}$$

$$\text{and destination, the origin and destination are in the same state}]$$

[21]

I begin by estimating a baseline model to represent the conditional expectation which takes the form of the following:

$$\text{share}_{ijt} = \alpha + \beta\text{demdiff}_{ij} + \gamma\text{demdiff}_{ijt} + \eta\text{distance}_{ij} + \theta\text{ethnicdist}_{ij} + \phi\text{industrydist}_{ij} + \delta\mathbb{1}_{(samestate)} +$$

$$\sum_{t=1}^{21}\tau_t + \sum_{i=1}^{76}\psi_i + \sum_{j=1}^{73}\lambda_j + \epsilon_{ijt}$$

[21] Interpret distance the same as difference ie how different racially and employment-wise the origin and destination are

where the variables are defined as:

$\tau_t, \psi_i, \lambda_j$ are quarter, origin, and destination fixed effects, respectively;

demdiff$_{ij}$ = ||average of the 2016 and 2020 Democratic vote share in the origin CSA i - an average of the 2016 and 2020 Democratic vote share in the destination CSA j|| ;

demdiff$_{ijt}$ =demdiff$_{ij}$ $\times$ Date ;

ethnicdist$_{ij}$ = $((\frac{totalwhite}{totalpop})_i-(\frac{totalwhite}{totalpop})_j)^2+((\frac{totalblack}{totalpop})_i-(\frac{totalblack}{totalpop})_j)^2+((\frac{totalhispanic}{totalpop})_i-(\frac{totalhispanic}{totalpop})_j)^2+((\frac{totalasian}{totalpop})_i-(\frac{totalasian}{totalpop})_j)^2+((\frac{totalother}{totalpop})_i-(\frac{totalother}{totalpop})_j)^2$;

industrydist$_{ij}$ = $((\frac{totalinsector1}{totalemployed})_i-(\frac{totalinsector1}{totalemployed})_j)^2+...+((\frac{totalinsector\mathbf{n}}{totalemployed})_i-(\frac{totalinsector\mathbf{n}}{totalemployed})_j)^2$

for origin-destination pairs ij.

The sectors in the industry variable are the 20 broadest NAICS categories, a list is presented in the data appendix as Table 4. Here, Date is a continuous variable and takes on the values of the first day of the fiscal quarters ranging from the first quarter of 2017 to the first quarter of 2022. It is important to note that I do not need to estimate a log of the dependent variable as the data is already in percent.

The above model leads to the first hypothesis:

Hypothesis 5.1. $\gamma > 0$*, or as time progresses, and WFH becomes feasible due to COVID-19, the more different the partisan alignment of the origin and destination is, the more likely people are to move. Equivalently as time progresses, we expect to see a larger share of people moving to places with different political affiliations.*

5.2 Baseline Estimates

To see regression results consult Table 6 in Appendix 3. Figure 6 in Appendix 3 plots the coefficients of interest in the baseline models while Figure 5, again, shows a visual trend of how the Democrat vote share difference (demdiff$_{ij}$) changes across the panel time series component. All models have robust standard errors clustered on the origin-destination pair level.

Table 6 shows the OLS coefficient estimates from five estimated models in each of its columns. The Nothing column is the linear model with only the Democrat vote share difference and Democrat vote share difference interacted with date variables. This model serves as the skeleton to which the proceeding columns add-on to.

The Indicators column estimates the Nothing column with the inclusion of the same state dummy. The RID column controls for the racial and industrial distance between the origin and destination as well as the physical distance between the origin and destination. The FE column estimates the Nothing column but with the inclusion of origin, destination, and quarter fixed effects.

The Baseline column is the model specified above, or the union of the Indicator, RID, and FE models.

As we move along the columns from left to right, we notice an increase in the adjusted R^2 and F-statistics.

First, notice that the variable of interest, Dem Difference × Date- which is that of demdiff_{ijt} - is significant for both the Fixed Effects and Baseline regressions. While only significant at the 90% level in the Baseline regression, the sign of the coefficient is positive, which corroborates Hypothesis 5.1. Specifically, these results tell us that we should reject the null hypothesis that the effect hypothesized in Hypothesis 5.1 is zero. In other words, there exists general political sorting in this time period.

What we can clean from these baseline results is that as the date progresses, or we go deeper into the panel, a citizen is more likely to move to a CSA with a different average Democrat vote share. In other words, as the COVID-19 pandemic manifests and the effects of WFH and restrictions are felt, the share of citizens move from one CSA to a different one, and the larger the gap in average Democrat vote share between the origin and destination increases.

Interesting in these results as well is the strong significance of the same state and distance between origin and destination variables. In both the RID and Baseline regressions, these two variables are significant at the 99.99% level but for apparently different reasons. The effect of distance between origin and destination is very small; the coefficient is zero until the thousandths and ten-thousandths of a decimal point but has a very small standard error. The effect of the same state is significant insofar as it has a more pronounced effect.

Of interest is that when the same state indicator is included in both the Indicators and Baseline models, it has approximately the same estimate and standard error. It is significant at the 99.99% level in both regressions. When it is not included, and the race, industry, and distance controls are, all of the significance from the same state is captured by distance and racial distance. When looking at the Baseline model, we see that when the same state is included, along with all the controls and fixed effects, distance retains its high explanatory power, but with a decreased magnitude. We also see that all of the explanatory power from a racial distance is captured by the same state. I discuss the reasons for this in the discussion section.

While the Baseline estimates are significant for the variable of interest, demdiff_{ijt}, it presents neither as much explanatory power as would be beneficial. Nor does it offer a breakdown of this effect in a manner to allow us to look at a specific time. It only offers a general trend. To get around this, I present the next modification.

5.3 Modification 1

The baseline regressions showed that there is a significant causal relationship between politics and moving. Moreover, as time progresses, this effect has more explanatory power. Where the baseline models fell short was their inability to show this effect at any given point in time.

Here I take the Baseline model and attempt to increase the explanatory power and specificity of the dynamic politics term by interacting the Democrat vote share difference variable with a categorical variable for the quarter. In the baseline model, I simply made demdiff_{ijt} the product of the two continuous date and dem vote difference variables. Now I specify a new variable as:

$$\text{dynamicdemdifference}_{ijt} = \text{demdiff}_{ij} \times \text{Quarter}$$

where Quarter is the categorical variable serving as the quarter fixed effects. By doing this, we can see how political difference motivates or demotivates people's decision to move by each quarter in the data set. This translates to the following modified baseline model:

$$\text{share}_{ijt} = \alpha + \beta\text{demdiff}_{ij} + \gamma\text{dynamicdemdiff}_{ij} + \eta\text{distance}_{ij} + \theta\text{ethnicdist}_{ij} + \phi\text{industrydist}_{ij} +$$

$$\delta\mathbb{1}_{(samestate)} + \sum_{t=1}^{21}\tau_t + \sum_{i=1}^{76}\psi_i + \sum_{j=1}^{73}\lambda_j + \epsilon_{ijt}$$

, with OLS estimates reported in Table 7 in Appendix 3.

This regression offers something akin to a "treatment effect decomposition" where we can see the effect that political difference between CSAs has on explaining the change in the share of people moving between two CSAs. We can see that as time progresses and the COVID-19 pandemic persisted, people were more likely to move to a CSA that was of a different political persuasion than their origin CSA. This is shown by all of the coefficients of interest being positive, showing that the larger the difference in the share of votes a Democrat received between an origin and destination, the share of people who moved from the origin to the destination increased.

More specifically, relative to the first quarter of the panel, January 1 2017-March 31, 2017, quarters 2-5 offer mild, if any, significant explanatory power. However, as the quarter progresses, we see a trend in not only statistical significance but in the magnitude of coefficients.

First and foremost, all interaction coefficients are positive, showing that relative to the first quarter of the panel, citizens are more likely to move to a CSA with a different Democrat vote share than their origin CSA. Secondly, these coefficients are increasing in magnitude, with the largest jump being from quarter 5 to quarter 6.

The results for the modified model again show that the same state is highly significant and has a similar coefficient to the baseline estimates. The estimate for distance between origin and destination is exactly the same estimate as the Baseline column in Table 6 but is again highly significant.

This modification allows us to see, compared to the first quarter of 2017, the effect that partisan difference had on movement decisions in each proceeding quarter was significant and positive. We also see that more citizens move to destination CSAs in the same state as the origin CSA and the farther away the destination, the less migration there was between that pair.

The racial and industrial controls are not significant, and the adjusted R^2 is only 0.01 less than that of the Baseline column in Table 6.

I have established that there is a dynamic effect of politics on the outcome of a citizen's movement decision. Specifically, I have demonstrated the effect we see of more people moving to more politically dissimilar destinations CSAs increase over time, not only continuously but categorically. Armed with the fact that this effect exists and is significant, we can proceed with the modification to find an empirical answer to Result 3.18.

5.4 Modification 2

To answer if Result 3.18 is corroborated by evidence, I utilize and modify the baseline model. I proceed by way of a triple interaction.

I proceed in this manner to exploit the natural experiment framework that COVID-19 created. By viewing the pandemic as the treatment, I am again able to decompose its effect, like in the first model modification, by using interactions. Specifically, I make use of two interaction variables defined later in this section.

It is important to comment on the specific empirical approach this modification employs. While being in the vein of a difference-in-difference approach (more accurately, a triple difference), it is nothing more than another interaction and fixed effects model.

This could not be considered a triple difference model for three reasons. First, the treatment, COVID-19, is uniform across all groups and is observed at the CSA and group level for all periods in the panel. Second, and most important, COVID-19 is time invariant in that no one CSA or group was affected by it while others were not in the same quarter. There is no need to observe the treatment on a level aggregated above the observational unit of grouped CSAs. The next reason being the estimates are not differenced. As will be apparent in the regression equation, I included origin, destination, and quarter fixed effects and interact with the Democrat vote share difference in pair *ij* with the COVID and group variables. I do not include the two interactions on their own as they are served by the fixed effects. The final reason is made apparent in Figure 8 in Appendix 3, which shows that the parallel trend assumptions fails as well. The migration rates of the four groups trend in the same direction but are subject to different fluctuations and slopes.

Using this experimental setting, the goal is to find unbiased estimates of the effect that politics has on movement between CSAs that present different wages and similar amenities, and vice versa, and no difference at different points in time. The intuition behind this is as follows: given that there exists a dynamic effect of politics on citizens' movement decisions, how does the effect compare across groups and points of time when the groups are based on their wage and amenity differentials?

To tackle this problem, I made use of two new categorical variables to interact with demdiff_{ij}. The first of these categorical variables partitions the time series aspect of the panel into the phases of COVID-19. This partition is more granular than the continuous date interaction and provides a more straightforward and accessible interpretation than the 21-quarter decomposition.

The second categorical variable corresponds to a partition of the origin-destination pairs. The partitions fall into four groups: those pairs where the origin and destination have a similar wage and different amenities, different wages and similar amenities, similar wages and amenities, and different wages and amenities. I present a more comprehensive treatment of this process, along with figures and tables in Appendix 4.

The two categorical variables are defined as follows:

$$\textbf{COVID} = \begin{cases} 1 & \text{for quarters 1-13} \\ 2 & \text{for quarters 14-16} \\ 3 & \text{for quarters 17-21} \end{cases}$$

which measures the three "phases" of COVID-19. These phases are pre-COVID, during COVID, and post-COVID, respectively. The notion is that in quarters 17-21, there will be more explanatory power in the dynamic average Democrat vote difference term, relative to pre-COVID.

$$\textbf{Group} = \begin{cases} 1 & \text{for similar wage, different amenities} \\ 2 & \text{for similar amenities, different wage} \\ 3 & \text{for roughly similar wages and amenities} \\ 4 & \text{for different wage and amenities} \end{cases}$$

Here the category definitions are straightforward. I take group 4 as the control with the theory implying that there will be an effect of the Democrat vote difference for group 1 but not group 2.

To make use of the natural experiment framework, the above group definitions will be interacted with the COVID variable. The result I am aiming to prove leads to a comparison to, or control group of, those origin-destination pairs with both different wages and amenities before COVID. In short, this means that all $\text{demdiff}_{ij,t}$ estimates will be compared to the control of $\text{demdiff}_{\{ij \in \mathbf{Group_4}, t=1\}}$ for origin-destination pair ij.

The model I will estimate is the following:

$$share_{ijt} = \alpha + \beta \text{demdiff}_{ij} + \gamma(\textbf{COVID} \times \textbf{Group} \times \text{demdiff}_{ij}) + \eta \text{distance}_{ij} + \theta \text{ethnicdist}_{ij}$$

$$+\phi \text{industrydist}_{ij} + \delta \mathbb{1}_{(samestate)} + \sum_{t=1}^{21} \tau_t + \sum_{i=1}^{76} \psi_i + \sum_{j=1}^{73} \lambda_j + \epsilon_{ijt}$$

where the hypotheses are as follows:

Hypothesis 5.2. $\gamma_{\{ij \in \mathbf{Group_1}, t \notin \mathbf{COVID_1}\}} \leq 0$ *as there will not be any political sorting under a wage differential*

Hypothesis 5.3. $\gamma_{\{ij \in \mathbf{Group_2}, t \notin \mathbf{COVID_1}\}} > 0$ *as there will be political sorting in an amenity differential.*

Hypothesis 5.4. $|\gamma_{\{ij \in \mathbf{Group_1}, t=3\}}| \geq |\gamma_{baseline}|$*, or the estimated political sorting among the group that theory predicts do politically sort, post COVID-19, will be greater than the baseline.*

The above model is estimated with the goal of decomposing the treatment effect of time and origin-destination differentials on political sorting. Specifically, I consider the treatment effect to be time and group and use the system of indicator variables to decompose the treatment effect into main and simple effects as follows:

$$share_{ijt} = \alpha + \beta \mathbf{X} + \tau_{ijt} \times \text{demdiff}_{ij} + \epsilon_{ijt}$$

where,

$$\tau_{ijt} = \textbf{Group} + \textbf{COVID} + \textbf{Group} * \textbf{COVID}$$

which allows for a broader interpretation of when and where we see political sorting.

Interpretation of the decomposed model are as follows:

1. α is the intercept
2. β is a vector of OLS coefficients for the matrix if covariates **X** which contains all variables not listed below
3. τ_{ijt} is the "treatment effect," which shows the effect of being in any of the groups on moving to a politically similar destination, likewise for being in any time period of the pandemic, called the simple effects. Importantly it also shows the effect of moving to a politically similar destination for any group at any time period, called the interaction or main effect.

In the language of the hypotheses, we can expect to see insignificant simple effects and significant main effects. Moreover, we would expect the main effects to be insignificant in periods 1 (pre-COVID) but significant in periods 2 and 3 (during and post-COVID).

See Table 8 in Appendix 3 for the results of the regression and Figures 9 and 10 for visualizations of the coefficients and an effects plot, respectively[22].

From the table, we see mixed results regarding hypotheses 5.2-5.4. The first column presents OLS estimates of the model without fixed effects, the second column presents OLS coefficient estimates of the model with fixed effects.

This results table presents evidence of if there does exist political sorting between the groups. We notice that group 1 pre and post-COVID are the only coefficients that are significant in both models. We interpret this as showing, relative to group 4 pre-COVID, that there was more migration between origin and destinations that differed politically in group 1. In other words, for CSAs that were similar along the wage dimension and different along the amenity dimension, there was more political sorting between those CSAs both before and after COVID than CSAs that differed along both dimensions before COVID.

More clearly, in both models, there is significant and causal evidence that there was political sorting between CSAs that differed in amenities but not wages both before and after COVID. The fixed effects column provides further evidence that, in fact, this political sorting in group 1 was present only during and after COVID, with more statistical significance to those estimates. There is also strong statistical evidence that Group 3 exhib-

[22]The effects plot serves as a way of interpreting the decomposed model's treatment effect

ited more political sorting before, during, and after COVID than did Group 4 before COVID.

What that evidence tells us is that for origin-destination CSA pairs which present differential amenities but not wages exhibit more political sorting during and after COVID than what was present between CSAs who have differential wages and amenities before COVID. Further, there is significant evidence that both before, during, and after COVID, origin-destination pairs that had neither different wages and amenities exhibited more political sorting than the baseline. Succinctly, for origins and destinations that have different amenities and similar wages or similar wages and amenities, we see strong evidence for political sorting.

There does not exist significant evidence for any political sorting among group 2. While the coefficient estimates are not of the sign hypothesized, there does not exist enough statistical evidence to say if the results are true.

In terms of our hypotheses, we can confidently reject the null hypothesis that there is not a non-zero effect between COVID, the amenity differential group, and political sorting. In other words, know that the estimates lead us to accept Hypothesis 5.3. We also accept Hypothesis 5.4. Given that there is an effect of COVID in the amenity differential group, comparing the estimates in column 2 to those in the Baseline column of Table 6, we see that the magnitude of the Group 1 Post-Covid interaction is greater in magnitude than that reported for the dynamic average Democrat vote share difference.

Furthermore, we fail to reject the null hypotheses that there is not a non-zero effect between COVID, the wage differential group, and political sorting. Thus we cannot trust our estimates and cannot draw a definitive conclusion regarding Hypothesis 5.2. In other words, we are unsure if there does exist political sorting between origins and destinations that differ along wages but not amenities.

Appeal to Figure 9 in Appendix 3 to see visualizations of these coefficient estimates, with accompanying confidence intervals.

These results are further contextualized in Figure 10, the interaction plot which decomposes the effect of group and COVID on people's migration decisions.

Interpretation of this plot is as follows. The y-axis presents the linear prediction or margins of COVID $\times$ group interactions on the share of migration (in percent). For any given unit on the x-axis, the distance between the points of the lines presents the simple effect of COVID on people's migration decisions. The midpoint along each of the lines between the 3 COVID periods presents the simple effect of being in a group on people's migration decisions. The slope of the line determines if there is an interaction effect between the two. From this, it is evident that, due to overlapping confidence intervals, non-parallel lines, and different midpoints, there does not exist simple (individual) effects of COVID and group. However, given the presence of an interaction effect between the two, we know that the simple effect estimates are misleading, and we should only interpret the main effect, or interaction, of group and Covid on migration decisions.

More specifically, due to the interaction, we cannot understand the effect of just being in a group regardless of the COVID period, and vice versa. We must interpret these effects as joint. Therefore, people's migration decisions were affected by both COVID and what group their origin and destination lie in. It is, however, unclear to what extent this was ameliorated or exacerbated by the political difference between the origin and destination. All that this plot shows is that movement decisions (here represented by the predicted margins) were affected by when during the pandemic they chose to move and how similar or different the destination was to the origin in terms of wage or amenities.

6 Discussion

Two things from the empirical results stand out as warranting discussion. The first is the significance of the same state variable, and the second is the interaction between both group assignments and the time period in the outcome of the movement decision.

All three models presented, the baseline linear and two modifications, include a dummy variable for if the origin CSA and destination CSA lie in the same state. When it is included, in all models, it is highly statistically significant ($p<0.01$), with and without fixed effects. This indicates that regardless of the controls and decomposition of the treatment of interest, there is the most effect of moving in the same state.

In Table 6, when the same state variable is excluded, and the race, industry, and physical distance controls are added, racial distance and physical distance take on strong significance. When the same state is included again, along with the distance controls, physical distance remains highly significant, while racial distance is no longer significant. That indicates the significance captured by the same state and racial distance are likely very similar. Moreover, racial distance does not capture all the significance of same state, but same state captures all the significance of racial distance. If there was variation explained by racial distance not explained by same state, racial distance would retain some of its significance.

What this conveys is that some factors in common between origins and destinations in the same state may drive migration between them. However, those are not significant on their own. More racial homogeneity between origins and destinations, on its own, is linked with more migration, but that is an uncontrolled for (omitted variable bias) effect from same state. As CSAs in the same states tend to share demographic compositions, which explains why not controlling for same state leads to significant racial effects.

The other result of interest is the lack of main effects between group and time on the effect of migration. As discussed in the previous section, Figure 10 conveys that when we decompose the treatment effect of politics on migration decisions, we can only ascertain a joint effect between origin-destination group and time. Moreover, we are unable to determine if any of these joint effects differ, other than being in a different amenity group across all three periods of the panel. Looking back at the treatment decomposition, following the specification of the last model, the above is equivalent to saying that contrast and OLS estimates for Group and Time are misleading and cannot be believed to be significant due to the significance of Group*Time.

What this tells us is that it was not enough to be in one group or the other to have migration to a politically different CSA induced. Nor was it enough to be in the middle of or the end of the pandemic. It was necessary to both be in a setting where the origin and destination were differentiated *and* the time was right. Equivalently, we can say that we would not see movement of this degree to a different CSA before the pandemic; nor, during and after the pandemic, would we see the scale of movement to CSAs that were the same along either amenities or productivity.

What these two interesting results show is that on top of mixed results in terms of the hypotheses, it may be the case that a bulk of the observed moves to politically dissimilar destinations were simply moves within states. These moves could have taken place for many reasons, including political reasons. The issue of attribution aside, given the large number of out-of-state moves showing some significant political moves, means that we cannot wholly discount political motivation for sorting in settings where present.

The significant interaction effect shows that the pandemic did, in fact, play an important role in movement. While those in the origin-destination group we would have expected to see politically, sort didn't do so until it was feasible. In other words, the pandemic, and the factors therein, allowed people to move.

6.1 Future papers/contributions to the literature using this analysis

1. Varying the types to be something other than political. Perhaps using this framework to explain aspects of the Great Migration, Westward Expansion, or white-flight/neighborhood segregation.

2. Formally define the movement process as some, likely stochastic, process and perform comparative statics insofar as who moves when and who knows what may alter city decision events or lead to different outcomes "off the equilibrium path" of this analysis.

3. Make use of how WFH disentangles the citizen and labor force equality, and depend-

ing on the differential, you see certain cities becoming more workers than residents. This likely has lots of applications or ways to contextualize the results further, especially with respect to the targeting of polices, what the local economy would become, the types of commercial services that would be offered, and the development (commercial and residential) that would happen, and what political and economic competition between cities would look like. This could look like city policies being more responsive to one group than another, say laborers than residents, and what that does to future movement decisions.

4. What do this movement process and the results about population, political sorting, wages, home prices, etc, tell us about the consistency of policy in a given city and what economic competition between cities will look like (what kinds of tax breaks/subsidies/favorable treatment will be offered to which types of businesses) based on the type of people that live in each city.

5. Which do people value more, amenities, productivity, or the political peer effects?

6. Structurally estimating the utility functions.

7. Formulate aspects of this as a discrete choice problem. This could tie in with point (2) but getting down to the individual level and going deeper into (4), (5), (6), and (7) to explain the individual's problem, what exactly they're maximizing, what their constraints are, and if there is room for random utility.

7 Conclusion

The COVID-19 pandemic forever changed the United States, with the effects being felt for years to come. The political effects are some of the most salient, in some cases leading to realignments of entire voting blocks. More significant than that, however, is the effect that the pandemic had on geographic political sorting. One important reason for this is that the pandemic presents a situation where mobility costs are negligible. Work-from-home is the predominant reason that movement was not as costly as before due to people being able to retain their jobs and telecommute.

I present theoretical evidence that, using modifications of Tiebout's framework, when origins and destinations differ along an amenity dimension, people would move between them to the jurisdiction closest to their political ideal, when mobility costs are negligible. I corroborate this with empirical evidence showing that is, in fact, the case where, within a group of origin-destination pairs that differ by amenities, there is political sorting during and after the COVID-19 pandemic.

Further evidence shows that political sorting, across the board and for all observations, increased as the pandemic began, raged, and ended. The evidence also shows that the pandemic created a perfect storm insofar as it was not enough to be in an origin-destination group where political sorting was predicted, but it had to be feasible. Further, it was not enough to be in or after the pandemic, it had to be the case that the origin and destination were in the right group and the pandemic had at least begun. That is evidence that movement, for political reasons, where predicted, was spurred on by the pandemic, showing that political movement, while present beforehand, was not realized until movement became much cheaper. In other words, in this paper, I present evidence that the pandemic lead to increased political sorting and geographic polarization due to its decrease in mobility costs.

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8.2 Data

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9 Appendix 1: Proofs [23]

Proof of Proposition 3.10

a) Suppose individual i moves from city 1 to city 2. There are three groups of people whose utility will be affected.

First, the net effect among the N_1 residents of city 1 except individual i is given by

$$\sum_{N_1\backslash i}[u(\mathbf{P}^*_{1\backslash i}|\theta_{\tilde{N}_1}) - u(\mathbf{P}^*_1|\theta_{\tilde{N}_1})] \geq 0 \tag{19}$$

which follows from (5). Intuitively this means that a city cannot be made worse off by adjusting $\mathcal{P}^*$ to maximize the welfare of the current residents. The remaining residents of city 1 minus citizen i are at least as better off in the aggregate under $\mathcal{P}^*_{1\backslash i}$ as they were under $\mathcal{P}^*_1$. Call that the argmax arrangement.

Second I must consider the net effect among the N_2 residents of city 2. This is given by

$$\sum_{N_2\backslash i}[u(\mathbf{P}^*_{2\backslash i}|\theta_{\tilde{N}_2}) - u(\mathbf{P}^*_2|\theta_{\tilde{N}_2})] \leq 0 \tag{20}$$

which likewise follows from (16).

Finally, I consider the effect effect on individual i in two components. From the myopic comparison of city 1 and 2:

$$u(\mathbf{P}^*_2|\theta_i) - u(\mathbf{P}^*_1|\theta_i) - m_i > 0 \tag{21}$$

which follows from (6) and (7). The other component is how their movement will change **P** in city 2:

$$u(\mathbf{P}^*_{2+i}|\theta_i) - u(\mathbf{P}^*_2|\theta_i) \tag{22}$$

Indeed, (20)+(22) equals:

$$\sum_{N_2\backslash i}[u(\mathbf{P}^*_{2\backslash i}|\theta_{\tilde{N}_2}) - u(\mathbf{P}^*_2|\theta_{\tilde{N}_2})] + u(\mathbf{P}^*_{2+i}|\theta_i) - u(\mathbf{P}^*_2|\theta_i) = \sum_{N_2}[u(\mathbf{P}^*_{2+i}|\theta_{\tilde{N}_2}) - u(\mathbf{P}^*_2|\theta_{\tilde{N}_2})] \geq 0 \tag{23}$$

by (16).

Intuitively this follows from the argmax argument. In aggregate, the residents of city 2, including i, are no worse off under $\mathbf{P}^*_{2+i}$ as $\mathbf{P}^*_2$. The initial change may harm the remaining residents but the gain to individual i must be more. Specifically, it must be of a magnitude such that it offsets the losses to the other residents for if not then $\mathbf{P}^*_{2+i}$ would not be selected by City 2 who chooses policies by (5).

[23]The proofs of propositions 3.15 and 3.17 lean heavily on the analogous proofs from Rhode and Strumpf. I modify their notation to match that of the theoretical analysis. I present the conclusions in a more general setting.

Therefore, the total effect is given by (19)+(20)+(21)+(22) > 0. This implies that welfare, net of moving costs, $W - m_i$, increases, thus W increases as m_i are zero.

b) If individual i moves under WFH, this may entice other residents to move. In a), it was shown that no matter the number of moves that occur, W increases. This, potentially stochastic, movement process ends in a finite number of moves (equivalently, there exists an equilibrium) because there are a finite number of feasible allocations $\mathcal{P}$ and each individual's expected order in the sequence of location decisions is finite[24]. No allocation can reoccur because W strictly increases with each move. $\square$

Proof of Proposition 3.13 This proposition can be re-framed as the following theorem: If preferences satisfy single peakedness and there exist two cities and two types of individuals, then migration obeying (6) and (7) will increase the distance between cities policies. Right now, the notation is crowded, I will clean it up upon getting feedback.

Call the cities 1 and 2 and the types L and R where $\mathbf{P}_L < \mathbf{P}_R$. Let N_j be the total number of people in city j, and let N_{j_i} be the total number of people of type i in city j. Given N_{j_L} and N_{j_R}, $\mathbf{P}_j$ will be set to where: $N_{j_L} u'_L(\mathbf{P}^*_j) = -N_{j_R} u'_R(\mathbf{P}^*_j)$. Note that $u'_L(\mathbf{P}^*_j) < 0 < u'_R(\mathbf{P}^*_j)$ and $d[u'_R(\mathbf{P}^*_j)/(-u'_L(\mathbf{P}^*_j))]/d\mathbf{P}^*_j < 0$.

Apply the implicit function theorem to see that $\mathbf{P}^*_1 = O(\frac{N_{1_L}}{N_{1_R}})$ where $O' < 0, O(0) = \mathbf{P}_R$ and $O(\infty) = \mathbf{P}_L$. An analogous argument shows that $\mathbf{P}^*_2 = O[\frac{(N_L - N_{1_L})}{(N_R - N_{2_R})}]$. If $\frac{N_{1_L}}{N_{1_R}} > \frac{N_A}{N_B}$ then $\mathbf{P}_L \leq \mathbf{P}^*_1 < \mathbf{P}^*_2 \leq \mathbf{P}^*_R$, or city 1 will be preferred by type L and city 2 by type R.

Migration that obeys (6) and (7) and increases in N_{1_L} and N_{2_R} causes stricter segregation and widens the difference between community policies: $\frac{d\|\mathbf{P}^*_2 - \mathbf{P}^*_1\|}{dN_{1_L}} > 0$ and $\frac{d\|\mathbf{P}^*_2 - \mathbf{P}^*_1\|}{dN_{2_R}} > 0$

$\square$

Proof of the immediate implication from (2): $N^*_1 > N^*_2$

To see this consider $N^*_1 = N^*_2 = \overline{\mathrm{N}}$. Then, given $A_1 > A_2$ and $\alpha_1 > \alpha_2$ it follows that the LHS of 2 > RHS. This follows from the fact that $w(\overline{\mathrm{N}}, \alpha_1) > w(\overline{\mathrm{N}}, \alpha_2)$ and equal populations imply equal net housing benefit and heterogeneity $G(N^*_1) = G(N^*_2)$.[25] Then, the task is to decrease the LHS and increase the RHS. It is clear that wage and housing utility must fall in City 1 and rise in City 2 to help equalize both sides. It is also clear that the magnitude of the heterogeneity term must increase in City 1 as to subtract more from the LHS than RHS of (2). Now, making use of the properties of wage, housing utility, and heterogeneity $W_N < 0$, $H_N < 0$, and $G_N > 0$, then it must be the case that in order for in City 1 the wage and housing utility to fall and heterogeneity, to increase is to increase the population. This then arrives at the conclusion that $N^*_1 > N^*_2$. $\square$

[24]For the further exposition, a possible extension, or further research I can derive the stochastic process and transition matrix to illustrate the mechanics of the movement process to further deepen the understanding of this model.

[25]City 1 is just as heterogeneous as city 2. City 1's positioning LRM to City 2 is irrelevant and indeterminate here.

Proof of Proposition 3.4

To verify this proposition assume wlog that $w(N_2^*, \alpha_2) > w(N_1^*, \alpha_1)$[26]. Then the RHS of (4) is greater than 0, implying LHS of (4) is also greater than zero. Then the magnitude of the LHS must fall to zero in order for (4) to become (5). Recall that $H_N < 0$ and $G_N > 0$. It is then clear that a reduction in LHS of (4) comes from an increase in N_1 and the corresponding decrease in N_2, so $\tilde{N}_1 > N_1^*$. A similar argument holds for the reverse situation in which $w(N_2^*, \alpha_2) < w(N_1^*, \alpha_1)$, leading to LHS<RHS. □

[26]This all hinges that on the case that LHS>RHS so the G term is not taking enough away and adding too much so we want to increase G_1 and decrease G_2 so that it subtracts more and adds less.

10 Appendix 2: Data

CSA	Frequency	Percent
Albany-Schenectady, NY	206	1.15
Albuquerque-Santa Fe-Las Vegas- NM	158	0.88
Appleton-Oshkosh-Neenah, WI	40	0.22
Asheville-Marion-Brevard, NC	21	0.12
Atlanta-Sandy Springs-Alpharetta, GA	253	1.42
Bloomington-Pontiac, IL*	4	0.02
Boise City-Mountain Home-Ontairo, ID	108	0.60
Boston-Worcester-Providence, MA-RI-NH	843	4.72
Cape Coral-Fort Myers-Naples, FL	297	1.66
Charlotte-Concord, NC-SC	441	2.47
Chattanooga-Cleveland-Dalton	29	0.16
Chicago-Naperville, IL-IN-WI	999	5.59
Cincinnati-Wilmington-Maysville, OH-KY	320	1.79
Cleveland-Akron-Canton, OH	407	2.28
Columbia-Orangeburg-Newberry, SC	133	0.74
Columbus-Auburn-Opelika, GA-AL*	3	0.02
Columbus-Marion-Zanesville, OH	395	2.21
Corpus Christi-Kingsville-Alice, TX	26	0.15
Dallas-Fort Worth, TX	681	3.81
Dayton-Springfield-Kettering, OH	43	0.24
Des Moines- Ames-West Des Moines, IA	97	0.54
Detroit-Warren-Ann Arbour, MI	577	3.23
Eau Claire-Menomonie, WI	6	0.03
Fayetteville-Sanford-Lumberton, NC*	61	0.34
Gainesville-Lake City, FL	6	0.03
Grand Rapids, MI	27	0.15
Green Bay, Shawano, WI	20	0.11
Greensboro-Winston-Salem-High Point, NC	196	1.10
Greenville-Spartanburg-Anderson, SC	169	0.95
Harrisburg-York-Lebanon, PA	124	0.69
Hickory-Lenoir-Morganton, NC	13	0.07
Houston-The Woodlands, TX	617	3.45
Indianapolis-Carmel-Muncie, IN	396	2.22
Jackson-Vicksburg-Brookhaven, MS	4	0.02
Jacksonville-St. Marys-Palatka, FL-GA	283	1.58
Kalamazoo-Battle Creek-Portage, MI	89	0.50
Kansas City-Overland Park, KS	287	1.61

Knoxville-Morristown-Sevierville, TN	104	0.58
Lansing-East Lansing, MI	63	0.35
Las Vegas-Henderson, NV	172	0.96
Lextington-Fayette-Richmond-Frankfort, KY	68	0.38
Lincoln-Beatrice, NE	23	0.13
Louisville/Jefferson County-Elizabethtown-Madison, KY-IN	50	0.28
Macon-Bibb County-Warner Robins, GA	2	0.01
Madison-Janesville-Beloit, WI	205	1.15
Milwaukee-Racine-Waukesha, WI	433	2.42
Minneapolis-St. Paul, MN-WI	477	2.67
Myrtle Beach-Conway, SC-NC	113	0.63
Nashville-Davidson-Murfeesboro, TN	490	2.74
New Orleans-Metairie-Hammond, LA-MS	174	0.97
New York-Newark, NY-NJ-CT-PA	915	0.97
North Port-Sarasota, FL	231	1.29
Omaha-Council Bluffs-Fremont, NE-IA	145	0.81
Philadelphia-Reading_Camden, PA-NJ-DE	680	3.81
Pittsburgh-New Castle-Weirton, PA-OH-WV	381	2.31
Portland-Lewiston-South Portland, ME	125	0.70
Portland-Vancouver-Salem, OR-WA	763	4.27
Raleigh-Durham-Cary, NC	153	0.86
Reno-Carson City-Fernley, NV	123	0.69
Rochester-Austin, MN	17	0.10
Rochester-Batavia-Seneca Falls, NY	226	1.27
Rockford-Freeport-Rochelle, IL	71	0.40
Saginaw-Midland-Bay City, MI	1	0.01
Salt Lake City-Provo-Orem, UT	389	2.18
Savannah-Hinesville-Statesboro, GA	33	0.18
Seatle-Tacoma, WA	1,007	5.64
South Bend-Elkhart-Mishawaka, IN-MI	124	0.69
Spokane-Spokane Valley-Coeur d'Alene, WA	97	0.54
Springfield, MA	43	0.24
Syracuse-Auburn, NY	131	0.73
Tallahassee, FL	4	0.02
Toledo-Findlay-Tiffin, OH	22	0.12
Tulsa-Muskogee-Bartlesville, OK	70	0.39
Virginia Beach-Norfolk, VA-NC	293	1.64
Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	1,017	5.69
Youngstown-Warren-Boardman, OH-PA	51	0.29

Table 1: List of all Combined Statistical Areas used in the empirical investigation. Note that * indicates the CSA is only an origin. Those without are both origins and destinations.

State	Frequency	Percent
DC	1,017	5.69
FL	821	4.60
GA	291	1.63
IA	97	0.54
ID	108	0.60
IL	1,074	6.01
IN	520	2.91
KY	118	0.66
LA	174	0.97
MA	886	4.96
ME	125	0.70
MI	757	4.24
MN	494	2.77
MO	287	1.61
MS	4	0.02
NC	885	4.95
NE	168	0.94
NM	158	0.88
NV	295	1.65
NY	1,478	8.27
OH	1,238	6.93
OK	70	0.39
OR	763	4.27
PA	1,185	6.63
SC	415	2.32
TN	623	3.49
TX	1,324	7.41
UT	389	2.18
VA	293	1.64
WA	1,104	6.18
WI	704	3.94

Table 2: List of all states used in the empirical investigation

Date(Quarter)	Frequency	Percent
112017(1)	468	2.26
412017(2)	576	3.22
712017(3)	575	3.22
1012017(4)	580	3.25
112018(5)	547	3.06
412018(6)	783	4.38
712018(7)	815	4.56
1012018(8)	799	4.47
112019(9)	918	5.14
412019(10)	726	4.06
712019(11)	717	4.01
1012019(12)	686	3.84
112020(13)	748	4.19
412020(14)	875	4.90
712020(15)	988	5.53
1012020(16)	956	5.35
112021(17)	1,045	5.85
412021(18)	1,157	6.48
712021(19)	1,247	6.98
1012021(20)	1,261	7.06
112022(21)	1,398	7.83

Table 3: All dates included in the panel. This table constitutes the time of observation for the time-series component of the panel. The date is the first day of each fiscal quarter, in parenthesis is the quarter of the panel the date corresponds to.

NAICS Industry
Agriculture, Forestry, Fishing, and Hunting
Mining, Quarrying, and Oil and Gas Extraction
Utilities
Construction
Manufacturing
Wholesale Trade
Retail Trade
Transportation and Warehousing
Information
Finance and Insurance
Real Estate and Rental and Leasing
Professional, Scientific, and Technical Services
Management of Companies and Enterprises
Administrative and Support and Waste Management and Remediation Services
Educational Services
Health Care and Social Assistance
Arts, Entertainment, and Recreation
Accommodation and Food Service
Other Services(except Public Administration)
Public Administration

Table 4: 20 Broadest North American Industry Classification System (NAICS) classification. The share of workers in each of these classifications in each CSA was used to calculate the industrial distance variable.

Variable	Obs	Mean	Std. dev.	Min	Max
date	17,865	12.63857	5.994517	1	21
origin	17,865	85.12236	46.3839	1	163
destination	17,865	83.52645	45.94127	2	163
Democrat Vote Share of Origin, 2016	17,865	.5007319	.095248	.2656845	.6391544
Democrat Vote Share of Origin, 2020	17,865	.5392108	.0901478	.27637	.6662943
Democrat Vote Share of Destination, 2016	17,865	.4838767	.1000881	.265648	.6391544
Democrat Vote Share of Destination 2016	17,865	.5215714	.0978156	.27637	.6662943
Origin State	17,865	26.16496	10.06093	8	41
Share of Moves to Destination j from Origin i	17,865	1.328128	6.509257	0	82.7
Destination State	17,865	25.49902	10.34548	8	41
Dem Share 2016	17,865	.4315156	.1586876	.1298759	.7959778
Dem Share 2020	17,865	.4640947	.1687224	.125772	.8021646
Population-2020	17,865	369839.2	398229.8	350	2265461
Average Democrat Vote Share in Origin 2016	17,865	.5007319	.095248	.2656845	.6391544
Average Democrat Vote Share in Origin 2020	17,865	.5392108	.0901478	.27637	.6662943
Average Democrat Vote Share in Origin	17,865	.5199714	.09217	.2712831	.6444854
Average Democrat Vote Share in Destination 2016	17,865	.4838767	.1000881	.265648	.6391544
Average Democrat Vote Share in Destination 2020	17,865	.5215714	.0978156	.27637	.6662943
Average Democrat Vote Share in Destination	17,865	.5027241	.09849	.2712831	.6444854
Absolute Value of the Difference in Average Democrat Vote Share Between Origin and Destination	17,865	.1201519	.0806843	0	.3693642
Date	17,865	542699.7	341912.1	112017	1012021
Dynamic Difference in Average Democrat Vote Share Between Origin and Destination	17,865	1.523587	1.349461	0	7.756648
Distance Between Origin and Destination	17,865	1396.619	1091.225	0	4170.842
Racial Distance	17,865	.051409	.0484865	0	.2954963
Industrial Distance	17,865	.0165752	.0158965	0	.1455172
Median Home Price in Origin	17,865	205866.1	75054.9	97700	381000
Median Household Income in Origin	17,804	57390.14	8761.938	40000	81000
Median Home Price in Destination	17,865	197242.7	70810.88	97000	381000
Median Household Income in Destination	17,865	55782.98	9012.449	40000	81000
Mean Rate of Migration Between Origin and Destination	17,865	1.328128	.5588013	.4912088	4.208333

Table 5: Summary Statistics of the Panel

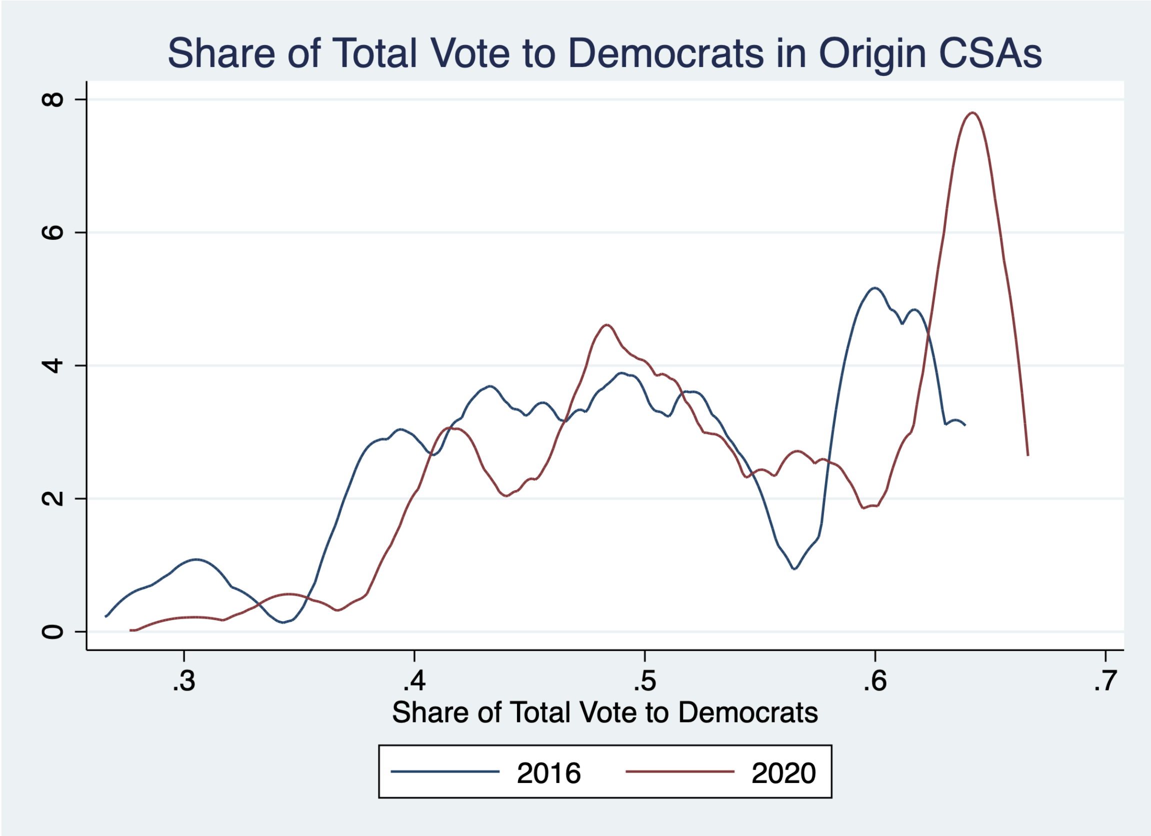

Figure 1: Share of total votes cast won by Democrats in 2016 and 2020 for all CSAs that are Origins.

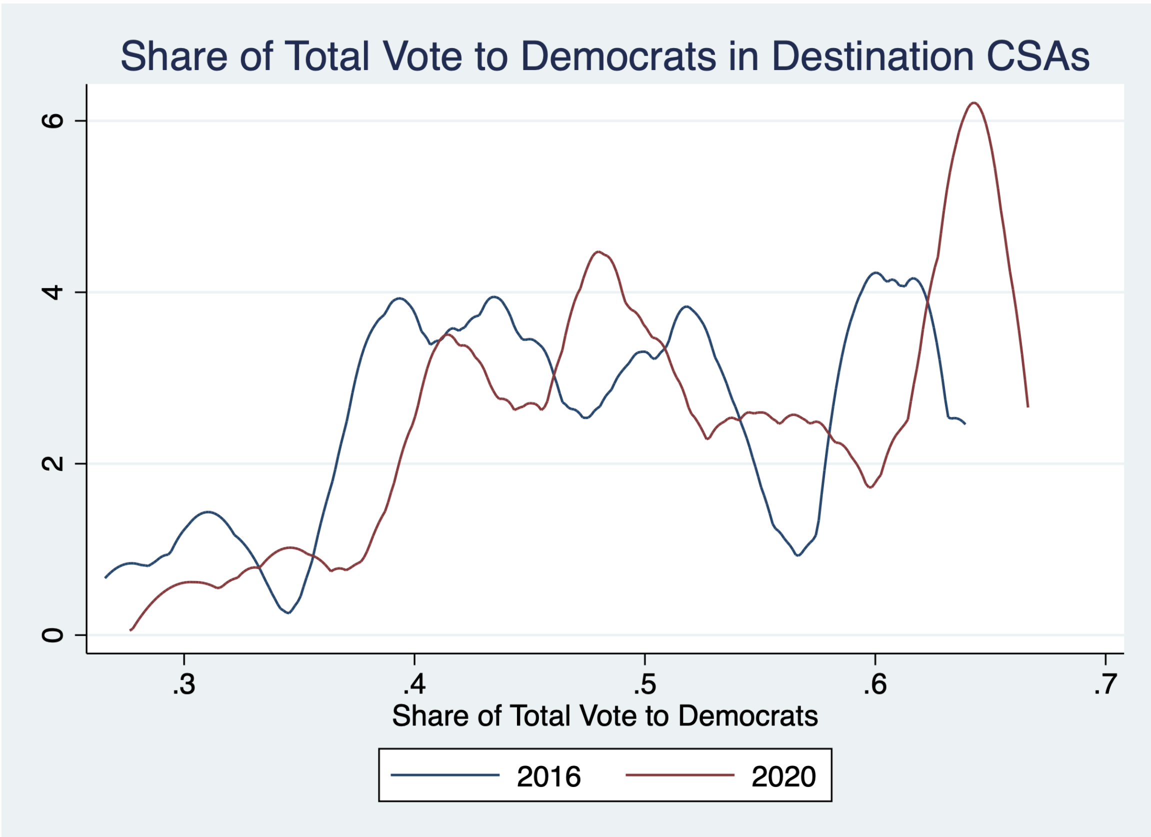

Figure 2: Share of total votes cast won by Democrats in 2016 and 2020 for all CSAs that are Destinations.

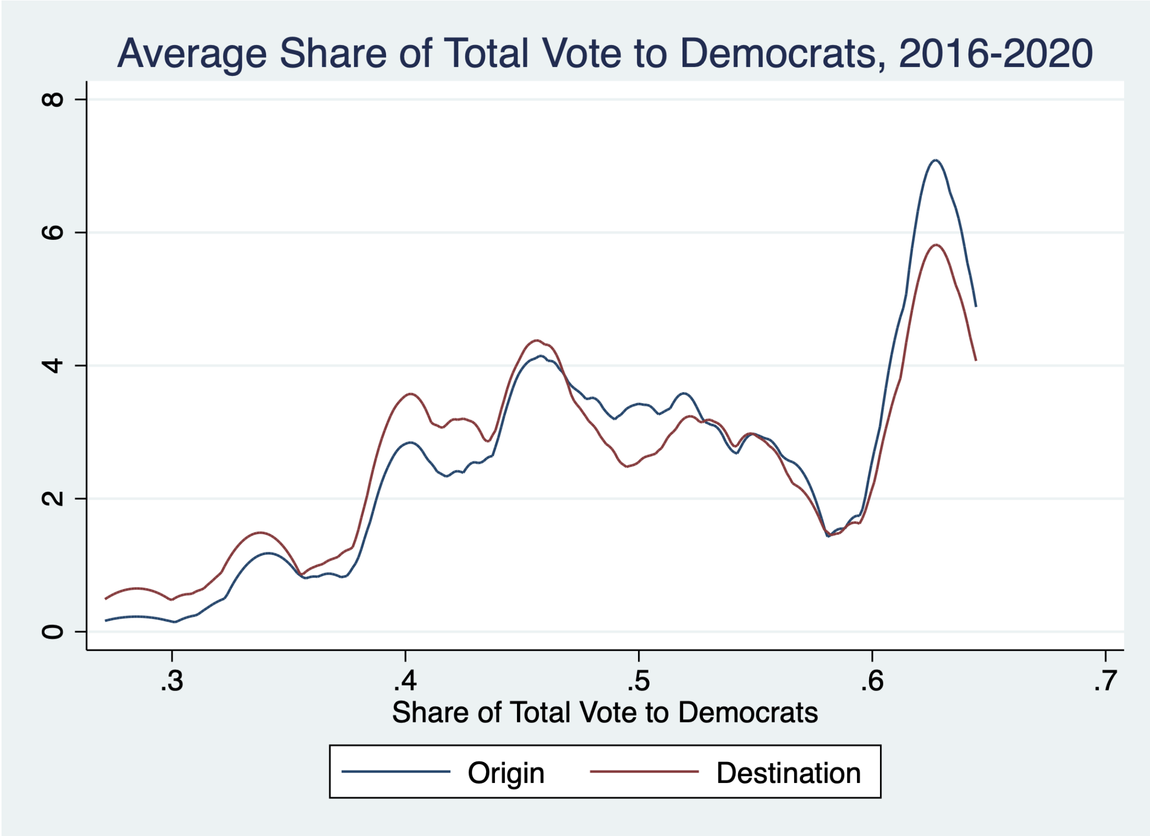

Figure 3: The average share of votes won by Democrats between 2016 and 2020 for Origin and Destination CSAs.

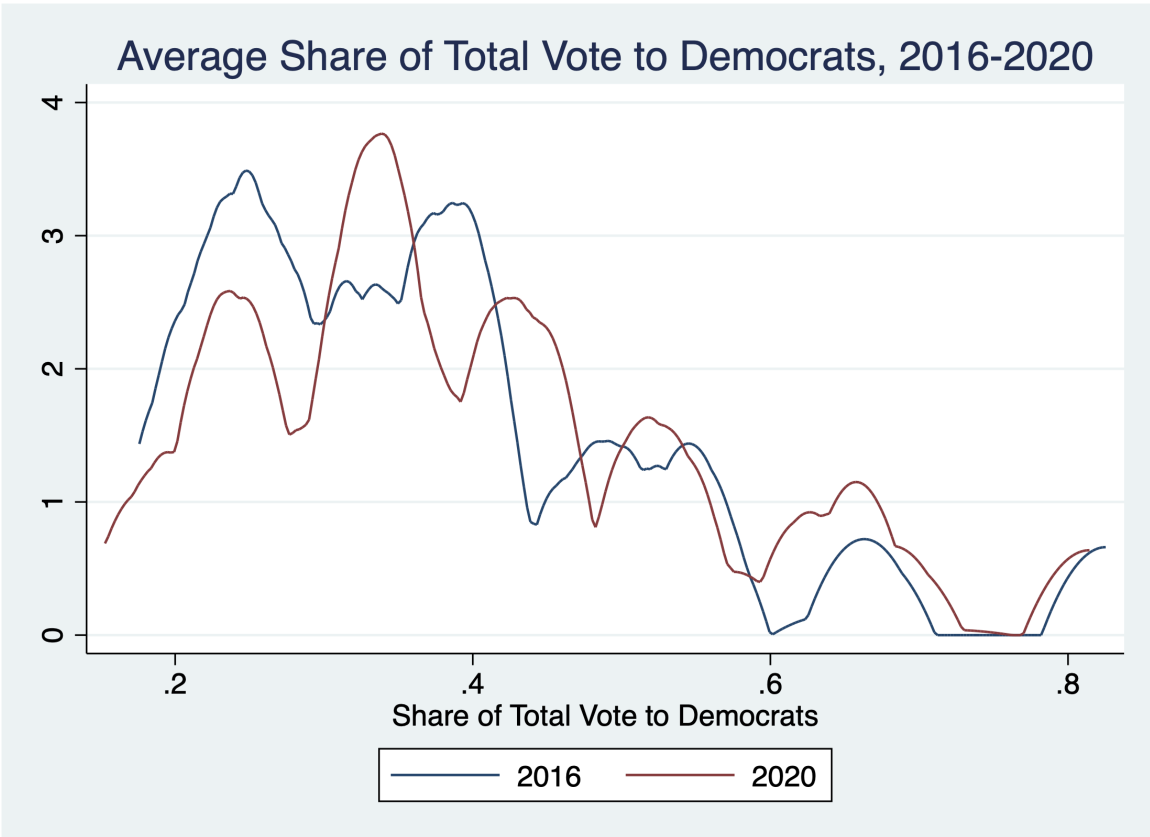

Figure 4: The average share of total votes won by Democrats across all CSAs in 2016 and in 2020.

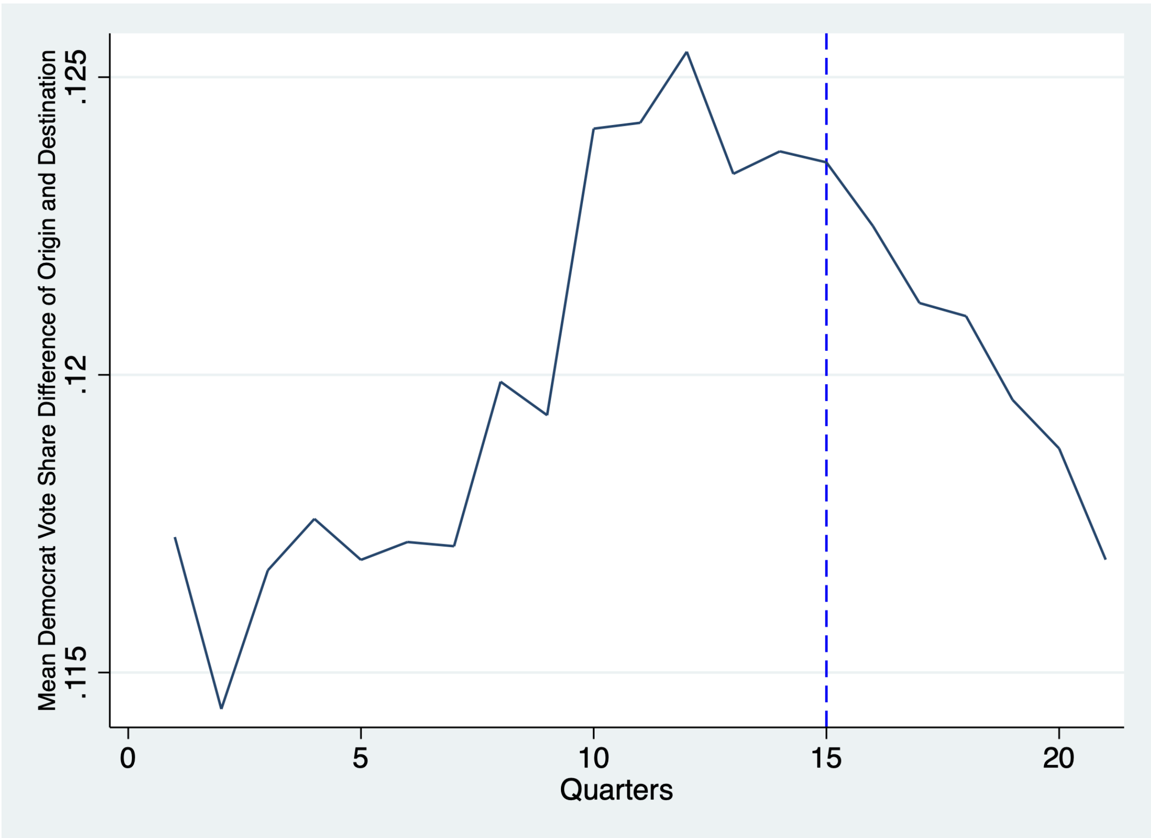

Figure 5: Time series of the average difference between average Democrat vote share at the origin and destination at each quarter.

11 Appendix 3: Results

	Nothing	Indicators	RID	FE	Baseline
Dem Difference × Date	0.0311	-0.0116	0.0103	0.5687**	0.4487*
	(0.0268)	(0.0326)	(0.0274)	(0.2817)	(0.2298)
Dem Difference	-6.5842*	-2.5690	-3.9429	-14.8219**	-8.6234
	(3.7222)	(2.7126)	(2.9072)	(7.2624)	(6.0912)
Same State		8.3048***			8.3020***
		(2.2455)			(2.3080)
Racial Distance			-7.8670***		-6.7749
			(2.8161)		(7.7112)
Industry Distance			-4.4906		17.5115
			(7.9549)		(22.1257)
Distance Between Origin and Destination			-0.0010***		-0.0007***
			(0.0002)		(0.0002)
Intercept	2.0719***	1.0097***	3.5983***	4.2467***	-0.5590
	(0.5882)	(0.3151)	(0.9377)	(1.2294)	(1.6022)
Fixed Effects	No	No	No	Yes	Yes
N	17,865	17,865	17,865	17,865	17,865
Adjusted R-squared	0.01	0.12	0.04	0.16	0.27
F	1.74	5.14	5.29	F(168,1820)	F(172, 1820)

Table 6: OLS estimates for the baseline model. *** p<.01, ** p<.05, * p<.1 Standard Errors in parenthesis. Standard Errors, robust and clustered on the origin-destination pair level, are reported in parenthesis. F-stat not reported by Stata in FE and Baseline models due to singleton FE observations. They are both appropriately large and indicate significant results when calculated using the appropriate degrees of freedom.

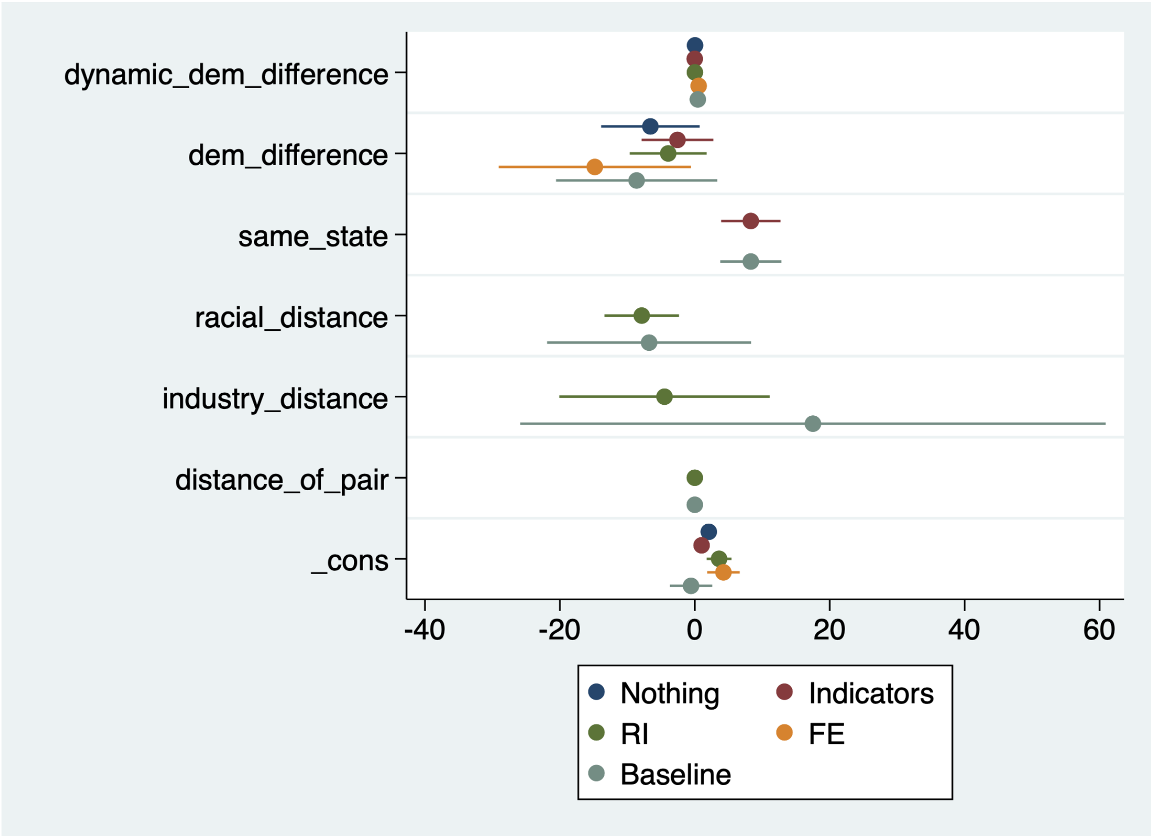

Figure 6: Visualization of non-fixed effects coefficients for the five baseline regressions.

	Modified Baseline
Dem Difference × Quarter	
2	1.7737
	(1.3014)
3	1.2183
	(1.2941)
4	3.2024*
	(1.9360)
5	1.7227
	(1.3172)
6	6.3363***
	(2.4396)
7	7.4124**
	(2.9324)
8	7.4468***
	(2.5930)
9	8.4715***
	(3.1780)
10	8.0490**
	(3.1240)
11	8.1845**
	(3.2296)
12	8.2532***
	(3.1437)
13	9.1792***
	(3.4046)
14	10.3940***
	(3.9662)
15	10.9900**
	(4.3593)
16	11.0712**
	(4.3189)
17	11.8478***
	(4.4544)
18	10.9369**
	(4.4510)
19	9.0960**
	(4.4931)
20	10.2046**
	(4.5061)

Table 7 continued from previous page

21	10.3866**
	(4.6233)
Dem Difference	-11.2285*
	(6.0038)
Same State	8.2975***
	(2.3087)
Racial Distance	-6.7885
	(7.7148)
Industry Distance	17.5329
	(22.1278)
Distance Between Origin and Destination	-0.0007***
	(0.0002)
Intercept	-0.1866
	(1.5850)
Fixed Effects	Yes
N	17,865
Adjusted R-squared	0.26
F	F(191,1820)

Table 7: OLS estimates for the baseline model. *** p<.01, ** p<.05, * p<.1 Standard Errors in parenthesis. Standard Errors, robust and clustered on the origin-destination pair level, are reported in parenthesis.

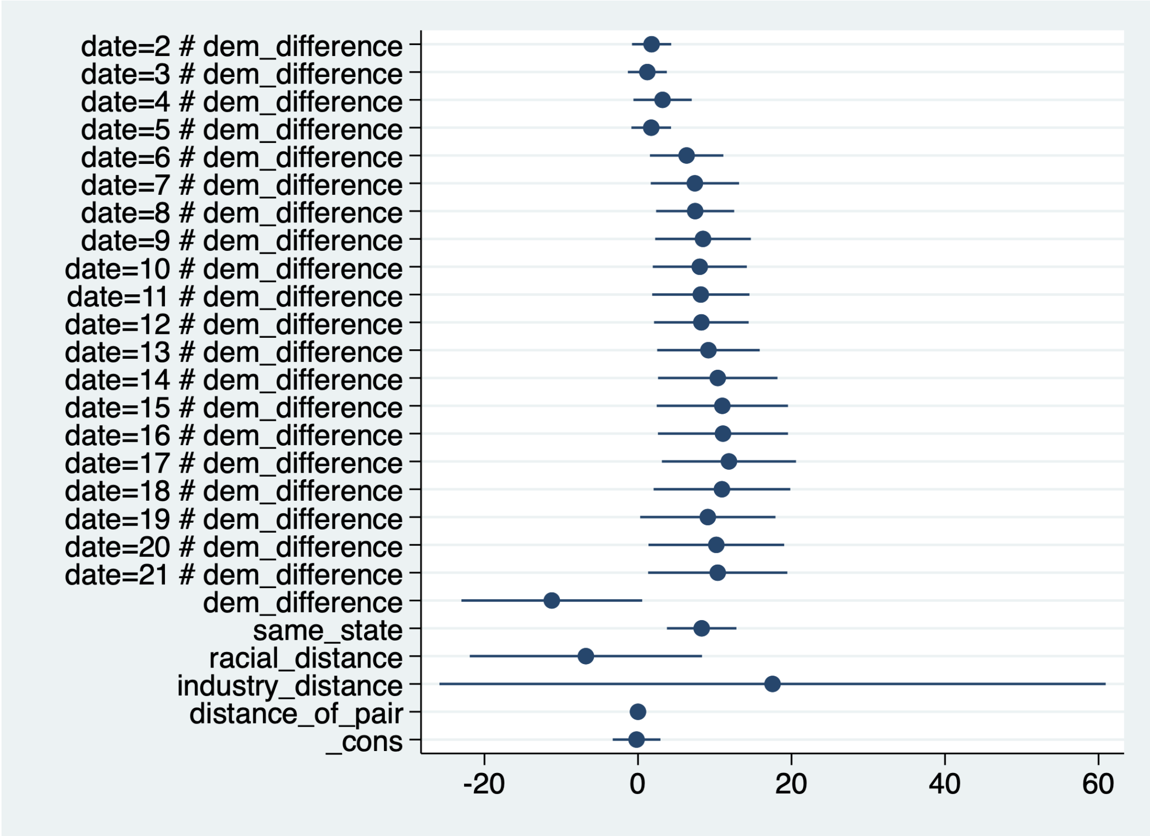

Figure 7: Visualization of coefficients for the modified Baseline model

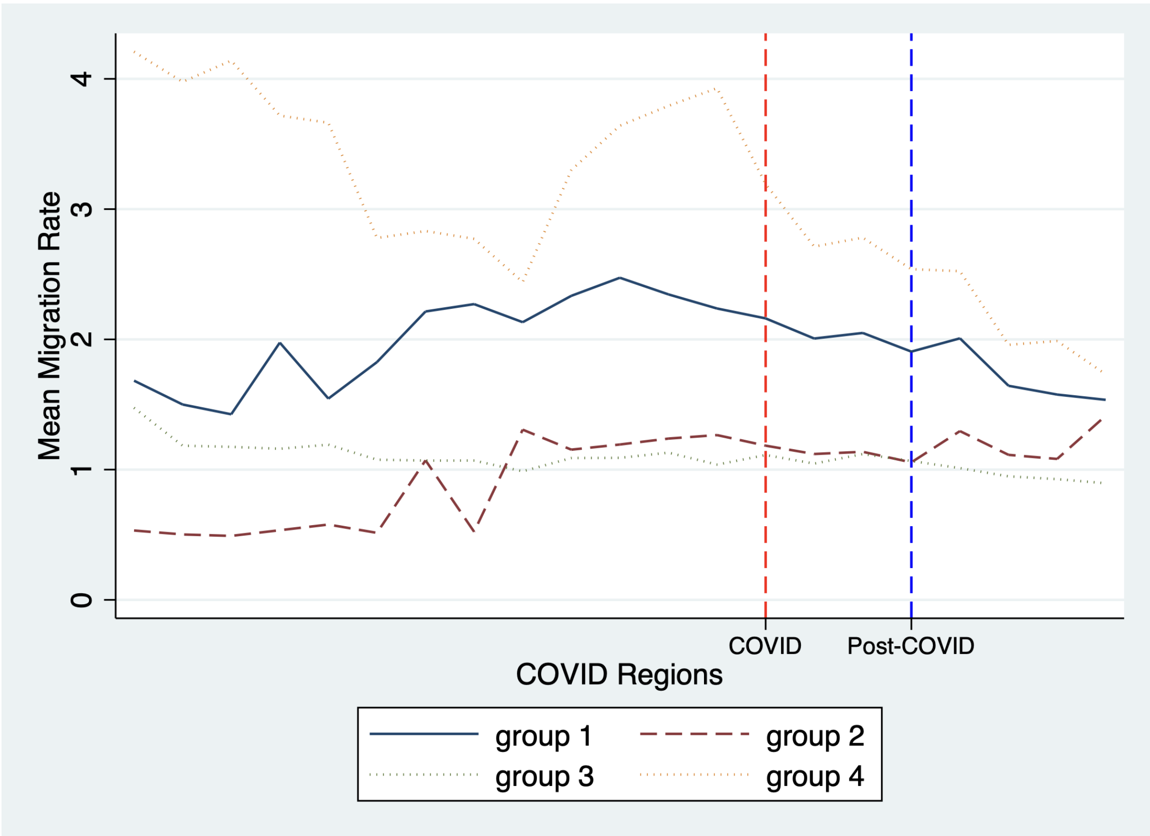

Figure 8: Trends in mean migration rates for each of the 4 partitioned groups. The three phases of COVID are delineated by the dashed lines, which name the period following their line.

	Interacted Model 1	Interacted Model 2
COVID×Group×Dem Difference		
Group 1 Pre-Covid	14.60156**	15.03817
	(6.194163)	(1.7053)
Group 2 Pre-Covid	1.075031	2.8640
	(4.23728)	(5.0835)
Group 3 Pre-Covid	6.60913	7.6235*
	(4.455484)	(4.3948)
Group 1 During Covid	15.44472**	19.6697***
	(6.504327)	(7.0498)
Group 2 During Covid	.2008847	.1689*
	(4.194953)	(5.2645)
Group 3 During Covid	6.856881	12.1545**
	(4.502468)	(5.2616)
Group 4 During Covid	2.212575	5.9362
	(3.818042)	(5.0304)
Group 1 Post-Covid	11.75217**	17.4580***
	(5.306756)	(6.5469)
Group 2 Post-Covid	.2816346	8.6566
	(4.377074)	(5.4639)
Group 3 Post-Covid	6.623153	12.3766**
	(4.506201)	(5.2616)
Group 4 Post-Covid	-2.065859	4.3224
	(3.277358)	(4.9352)
Dem Difference	-9.9085*	-14.0374**
	(5.4521)	(6.8966)
Same State	7.8382***	8.4066***
	(2.2028)	(2.3185)
Distance of Pair	-0.0004***	-0.0007***
	(0.0001)	(0.0002)
Racial Distance	-5.0528**	-7.1653
	(2.0689)	(7.7356)
Industrial Distance	-3.5506	12.0852
	(7.2960)	(21.8433)
Intercept	1.9018***	-0.6752
	(0.4685)	(1.6468)
Fixed Effects	No	Yes
N	17,865	17,865
Adjusted R-squared	0.13	0.27
F	2.65	F(182,1820)

Table 8: OLS estimates for the baseline model. *** p<.01, ** p<.05, * p<.1 Standard Errors in parenthesis. Standard Errors, robust and clustered on the origin-destination pair level, are reported in parenthesis.

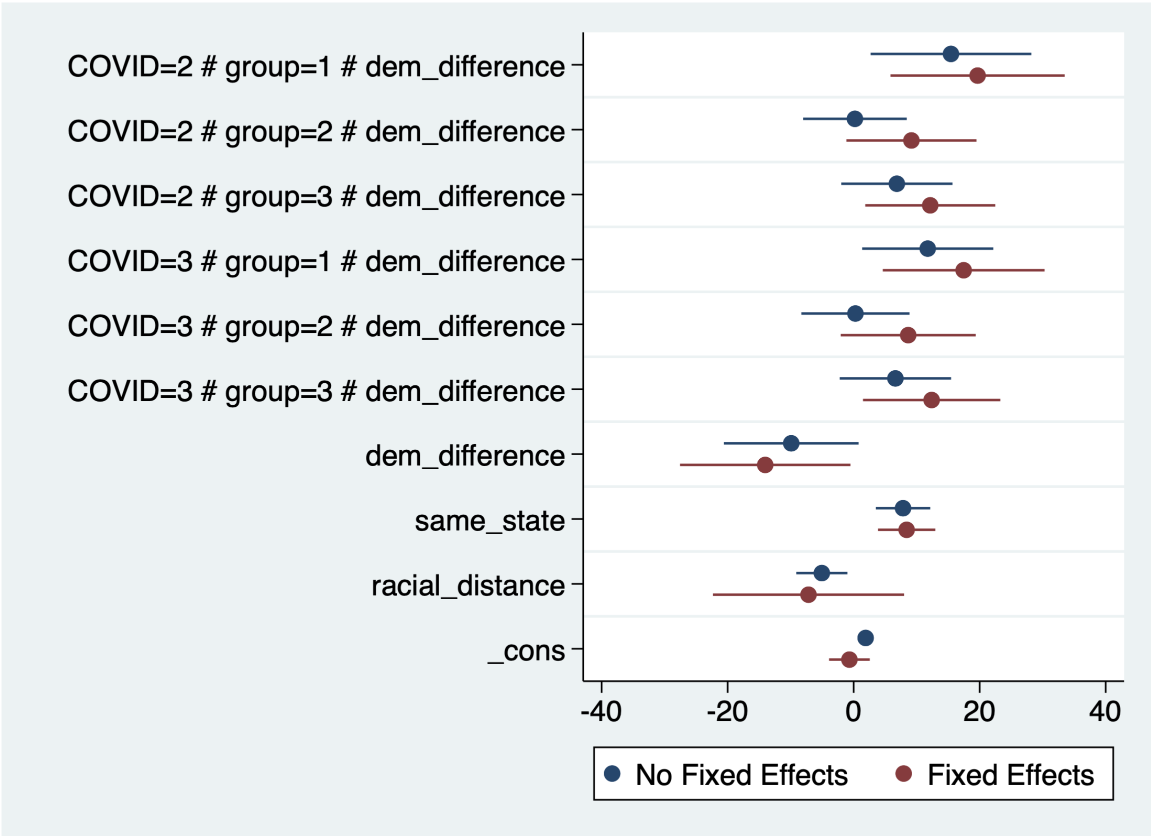

Figure 9: Visualization of non-fixed effects coefficients for the Triple Interaction Modification of the Baseline model

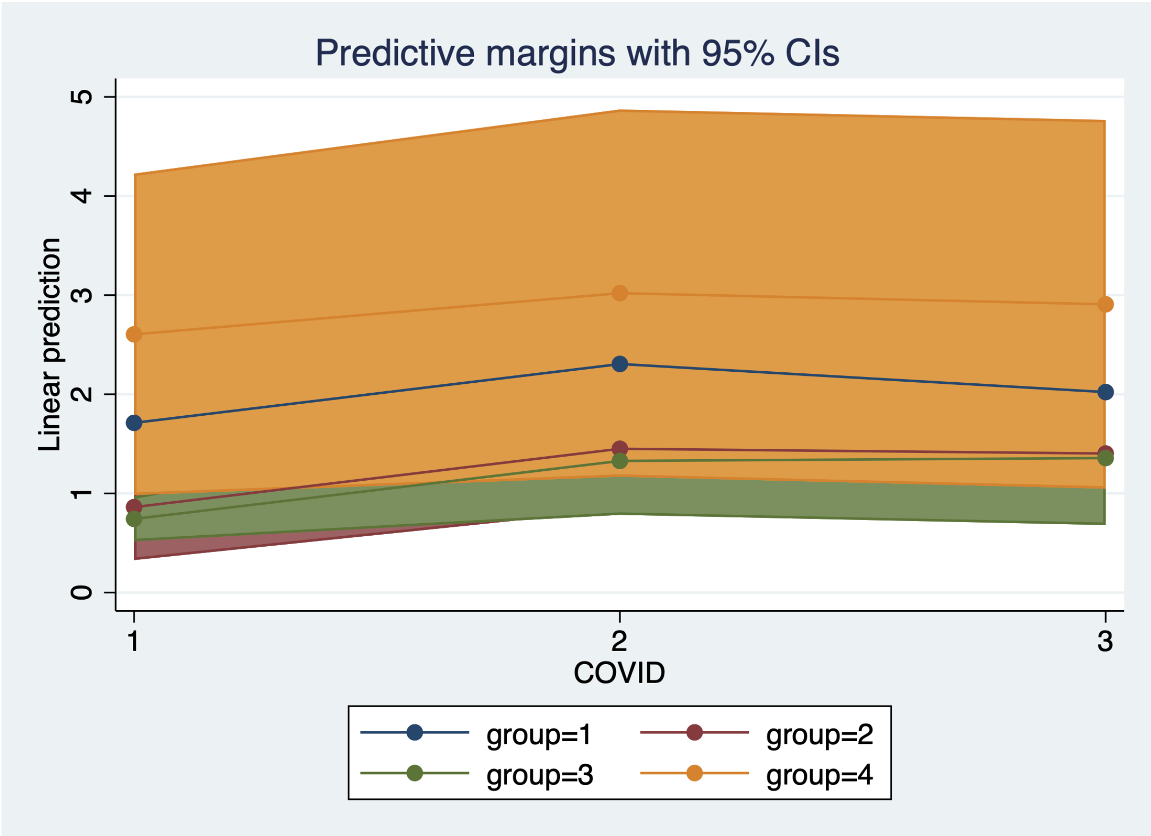

Figure 10: Effects Plot, shows the Simple Effects of COVID and group as well as the Main(Interaction) Effect of COVID × group. Confidence Intervals are areas shaded with a color corresponding to the group line

12 Appendix 4: Partition & Amenity Rankings

A fundamental aspect of the empirical analysis present in this paper is the grouping of origin-destination pairs. This appendix discusses the reasoning and methodology by which that was done.

The main result of the empirical analysis is the testing of Result 3.19. To test this hypothesis, I had to modify the baseline model in a way that would measure the effect of political differences in either of the differential cases. Moreover, I had to account for this effect temporally. This led to the introduction of the COVID and group categorical variables, stemming from the logic that the "treatment" effect of interest could be decomposed by interacting the average Democratic vote share difference by the two variables. This would then provide estimates, relative to the baseline, of the effect political difference between origins and destinations had on movement at each phase of COVID and in each differential.

To define the COVID categorical variable, I divided the time series component of the panel into three phases, roughly corresponding to demarcations in the COVID pandemic. I defined the pre-COVID period as all quarters before quarter 14, which began on April 1, 2020. I then defined quarters 14-16 as the COVID phase, or the height of the pandemic. I chose period 17 as the beginning of the post-COVID period due to that beginning on October 1, 2020, and covering a general decrease in the number hospitalized and the announcements from Pfizer and Moderna that they were seeking FDA approval for vaccines that were over 90% effective. These divisions are purely arbitrary, and there exist N good arguments for defining them differently from the N people one can ask.

To capture this differential effect, I proceeded to partition the sample of origin-destination pairs into four groups. This was to create the categorical Group variable such that if an origin-destination pair was in group 1, that mimicked the amenity differential, likewise for group 2 and the wage differential. For completeness, Groups 3 and 4 represented no differentials and double differentials, respectively. The wage differential is identical in interpretation to that of the productivity differential. I follow a common thread in the literature whereby I use wage as a proxy for productivity.

This partition made use of two rankings of each CSA. More specifically, ranking them by wage and amenity quartiles. This was accomplished in two phases.

First, the wage quartiles. I began with the median household income for each CSA. This measure was more consistent and reliable than the median wage. I preceded to partition the ranges of median origin and destination incomes into quartiles. Using the unique origin and destination IDs, I assigned to each origin-destination pair their median origin and destination household incomes and origin and destination wage percentile. I then ordered the origin CSAs in descending order according to percentiles, thus generating a ranking [27]. I then generated a variable called wage identifier which was defined by the difference in origin wage percentile and destination wage percentile. If the wage identifier was not equal to zero for a given origin-destination pair, then they exhibited a wage (read productivity) differential.

The manner by which I partitioned according to amenities was more complicated. Once I was able to rank CSAs by their amenity quartile, I could proceed with an amenity identifier in a manner similar to that of wage. However, it was not straightforward to generate the amenity quartile of a subset of CSAs. I then constructed a novel and, best as I can tell, the first of its kind in the literature, ranking of CSAs by amenities following the methodology from Glaeser, et. al. 2000.

In their paper, Glaeser et. al. construct an "amenity index" by regressing log housing prices on log per capita income with the belief that the residuals reflect the demand for local amenities. I proceed in this vein but with some minor modifications.

I first choose to use median household income instead of per capita wage. The reasoning for this is that this measure is less variable than per capita wage, is more readily available, and income is a broader term to reflect income that one receives either from work or not. Using income simply provides a more complete picture of one's fiscal situation and captures income such as that gained from rental properties. The second modification I make is the use of median house prices. Glaeser et. al. are unclear as to if they use mean, median, or weighted mean housing prices. To account for the likelihood that the distribution of home prices is skewed both within and between CSAs I use the median home price in each CSA as measured in 2020.

The next step was to estimate the following model for both the set of origins and destinations:

$$\ln(\text{median housing price})_i = \alpha + \beta \ln(\text{median wage})_i$$

where i is the origin or destination. I proceed to save the residuals of both regressions. Residual vs fitted values plots for both regressions are included as Figures 11 and 12 in the appendix of this appendix (Appendix 4.A). Both residual vs fitted values plots show exceptional model fitting from the above regression.

In an attempt to visualize the demand behavior for amenities, I provide, for each regression, scatter plots of the residuals vs median household income with a linear best-fit line. Overlaid on the scatter plot is the linear best-fit line to explain the residuals given an argument of median household income. Given the definition of a Hicksian demand curve, we can understand the trend line to be our best estimate of the demand curve for amenities

[27] I did this as the origin list is more complete and thus ranks all CSAs in the panel. This ranking mirrored those that are easily attainable via an online search engine and is thus omitted here.

at a given level of median household income.

Armed with these saved residuals for each CSA in both regressions, we can proceed like in the wage example. Match the residuals to each origin and destination in a given pair using the unique origin and destination IDs. From there, I again partitioned the range of residual values for the origins and destinations into quartiles. I then ordered in descending order the origin CSAs. This ranking is shown in Table 14 in Appendix 4. A. As far as I can tell, a ranking this complete of CSAs using this methodology is a new contribution to the literature and a novel way of beginning to understand the relationship between amenities, property values, and desirability of places to live.

After obtaining a ranking of the CSAs, I executed the same algorithm as before, where I made an amenity identifier, defined as the absolute difference in the amenity quartile of the origin and the destination. If this variable is equal to zero, then there does not exist an amenity differential. If it did not equal zero, then there was some manifestation of an amenity differential. It was infeasible given the time constraint and beyond the scope of this thesis to modify this analysis to allow for subgroups, one where a move is to a CSA that is more amenities and a move to a CSA that is less amenitied. Pursuing this avenue is potentially fertile ground for my future research.

12.1 Appendix 4.A

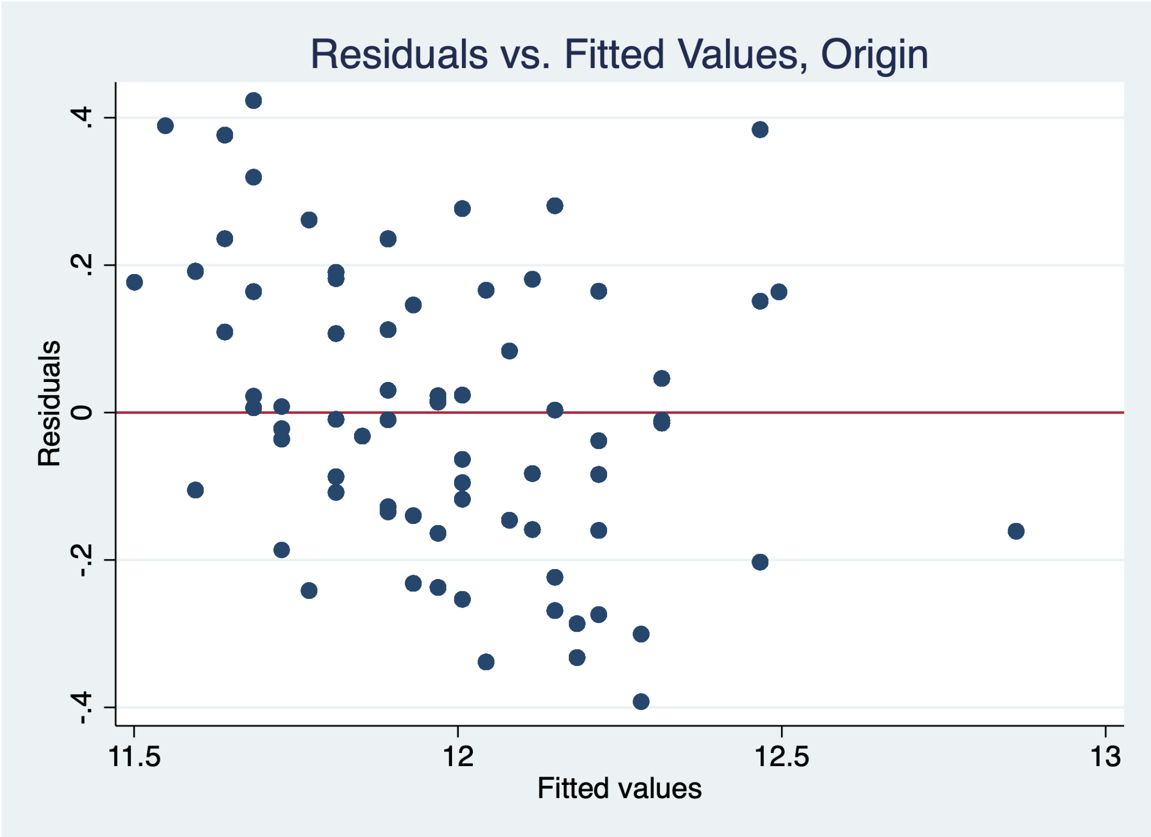

Figure 11: Residuals vs Fitted Values of ln(median housing price)$_i$ $= \alpha + \beta$ln(median wage)$_i$ for $i \in \{OriginCSA\}$

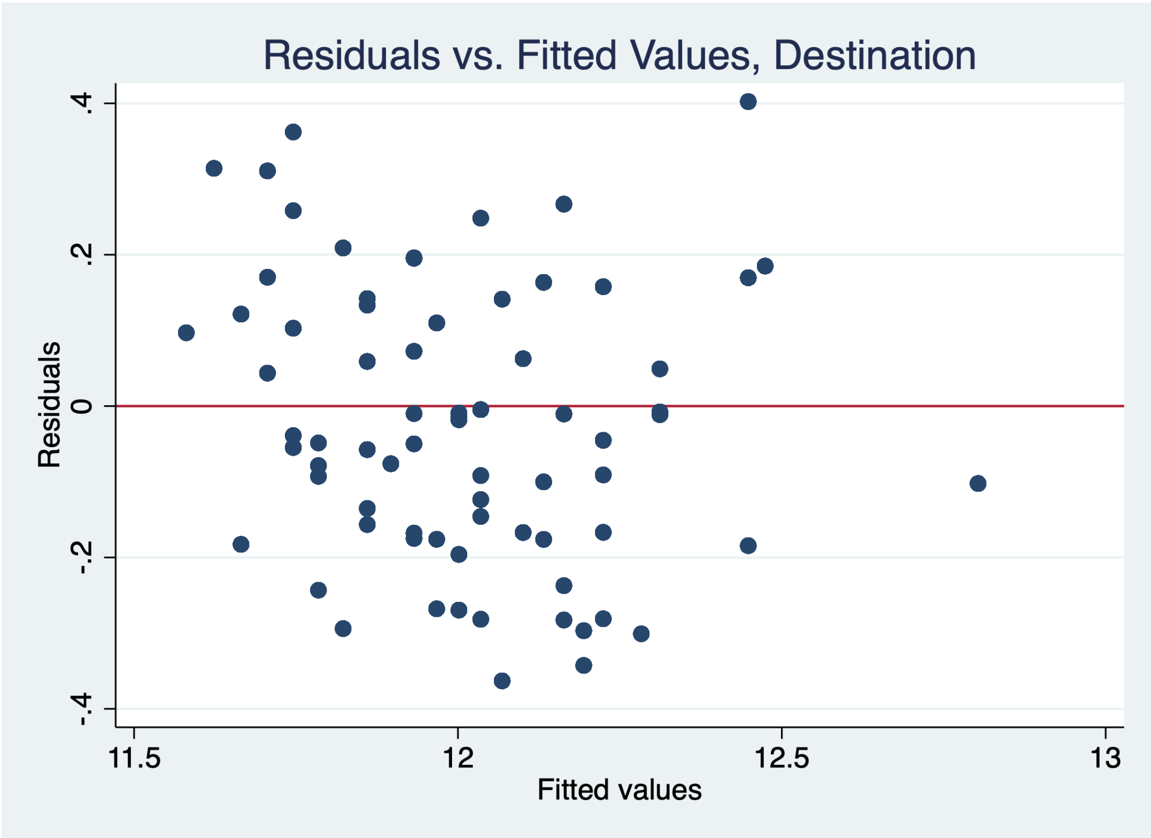

Figure 12: Residuals vs Fitted Values of ln(median housing price)$_i$ $=\alpha+\beta$ln(median wage)$_i$ for $i \in \{DestinationCSA\}$

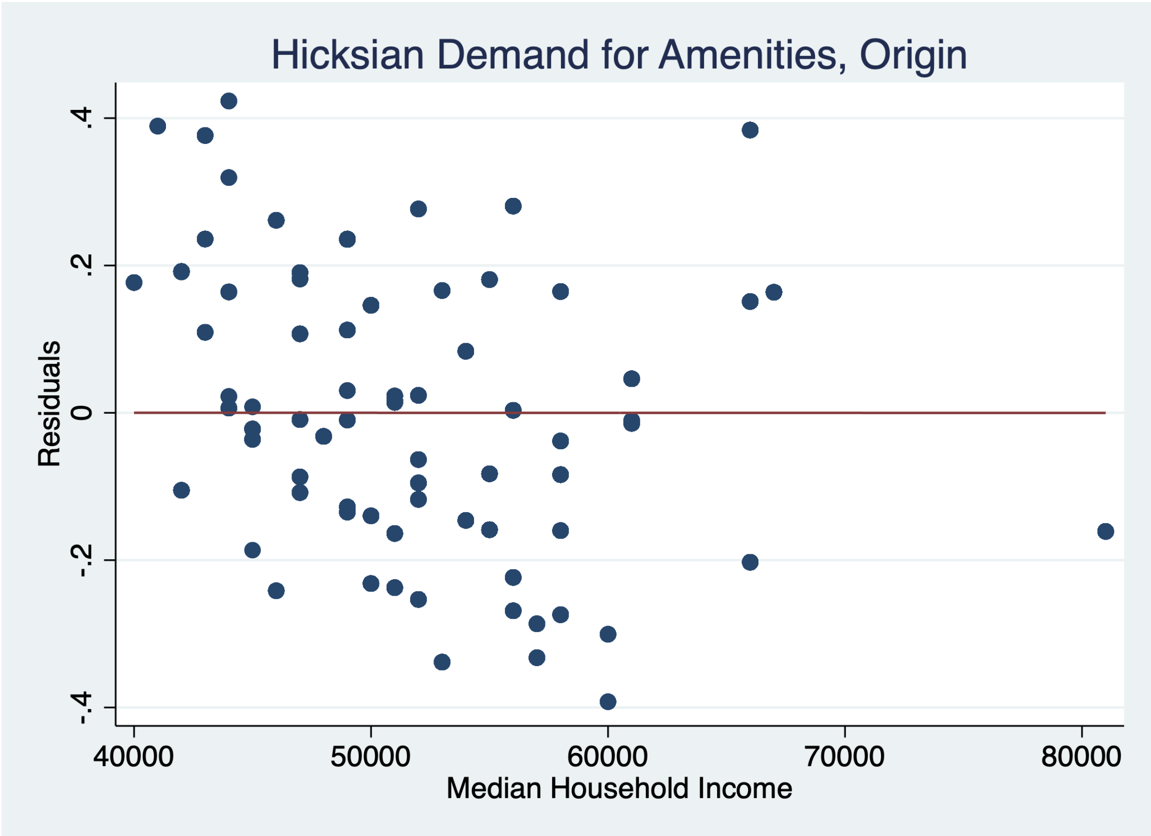

Figure 13: Estimate of the Hicksian Demand for amenities at a given level of household income. Visualized by the linear best-fit line between origin median household income and residuals of ln(median housing price)$_i$ =α + βln(median wage)$_i$ for $i \in \{OriginCSA\}$

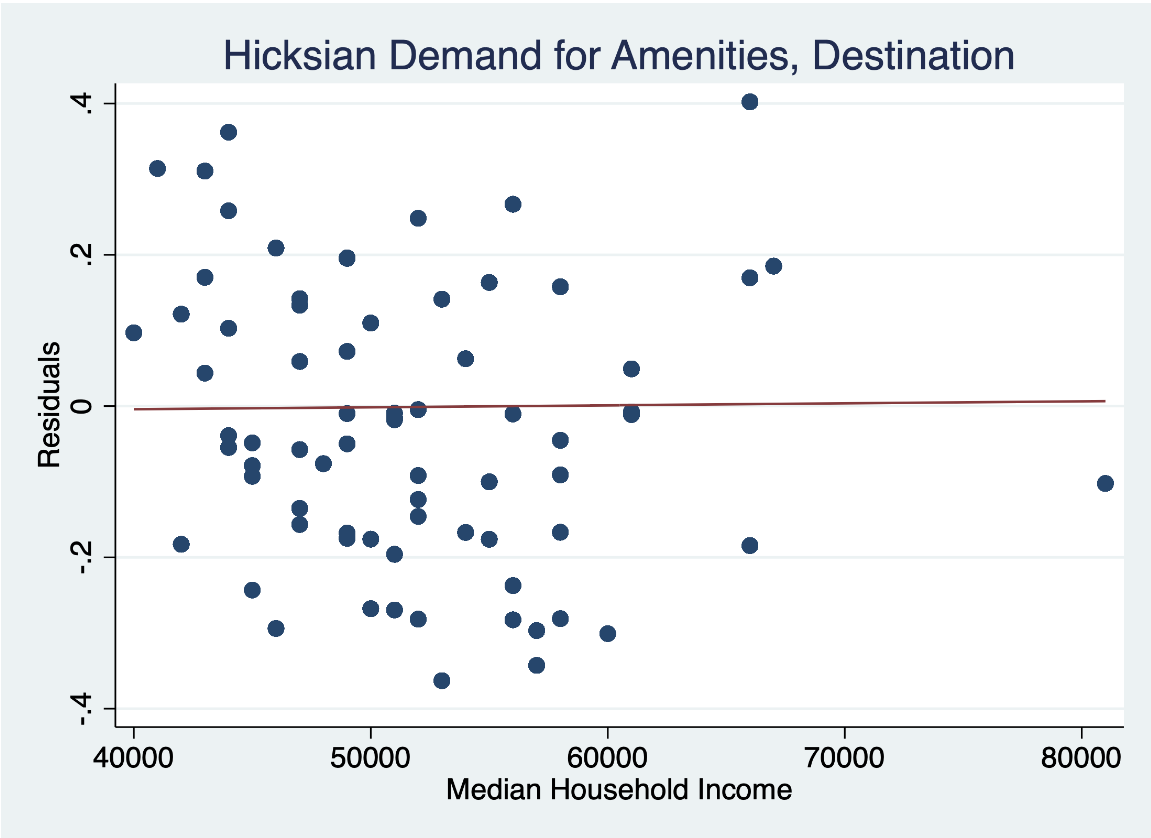

Figure 14: Estimate of the Hicksian Demand for amenities at a given level of household income. Visualized by the linear best-fit line between origin median household income and residuals of ln(median housing price)$_i$ =α + βln(median wage)$_i$ for $i \in \{DestinationCSA\}$

CSA Name
1st Amenity Quartile
Appleton-Oshkosh-Neenah, WI CSA
Bloomington-Pontiac, IL CSA
Corpus Christi-Kingsville-Alice, TX CSA
Dallas-Fort Worth, TX-OK CSA
Des Moines-Ames-West Des Moines, IA CSA
Detroit-Warren-Ann Arbor, MI CSA
Houston-The Woodlands, TX CSA
Indianapolis-Carmel-Muncie, IN CSA
Minneapolis-St. Paul, MN-WI CSA
Omaha-Council Bluffs-Fremont, NE-IA CSA
Pittsburgh-New Castle-Weirton, PA-OH-..
Rochester-Austin, MN CSA
Rochester-Batavia-Seneca Falls, NY CSA
Saginaw-Midland-Bay City, MI CSA
Syracuse-Auburn, NY CSA
Washington-Baltimore-Arlington, DC-MD..
2nd Amenity Quartile
Albany-Schenectady, NY CSA
Atlanta-Sandy Springs-Alpharetta, GA ..
Chicago-Naperville, IL-IN-WI CSA
Cincinnati-Wilmington-Maysville, OH-K..
Cleveland-Akron-Canton, OH CSA
Columbus-Marion-Zanesville, OH CSA
Dayton-Springfield-Kettering, OH CSA
Grand Rapids, MI
Green Bay-Shawano, WI CSA
Harrisburg-York-Lebanon, PA CSA
Kansas City-Overland Park-Kansas City..
Lansing-East Lansing, MI Metro Area
Lincoln-Beatrice, NE CSA
Madison-Janesville-Beloit, WI CSA
Rockford-Freeport-Rochelle, IL CSA
Salt Lake City-Provo-Orem, UT CSA
South Bend-Elkhart-Mishawaka, IN-MI CSA
Toledo-Findlay-Tiffin, OH CSA
Tulsa-Muskogee-Bartlesville, OK CSA
Youngstown-Warren-Boardman, OH-PA Met..
3rd Amenity Quartile
Boise City-Mountain Home-Ontario, ID-..

Cape Coral-Fort Myers-Naples, FL CSA
Charlotte-Concord, NC-SC CSA
Columbia-Orangeburg-Newberry, SC CSA
Eau Claire-Menomonie, WI CSA
Greenville-Spartanburg-Anderson, SC CSA
Jackson-Vicksburg-Brookhaven, MS CSA
Jacksonville-St. Marys-Palatka, FL-GA..
Kalamazoo-Battle Creek-Portage, MI CSA
Las Vegas-Henderson, NV CSA
Lexington-Fayette–Richmond–Frankfort..
Louisville/Jefferson County–Elizabet..
Macon-Bibb County–Warner Robins, GA ..
Milwaukee-Racine-Waukesha, WI CSA
Nashville-Davidson-Murfreesboro, TN CSA
Philadelphia-Reading-Camden, PA-NJ-DE..
Raleigh-Durham-Cary, NC CSA
Seattle-Tacoma, WA CSA
4th Amenity Quartile
Albuquerque-Santa Fe-Las Vegas, NM CSA
Asheville-Marion-Brevard, NC CSA
Boston-Worcester-Providence, MA-RI-NH..
Chattanooga-Cleveland-Dalton, TN-GA CSA
Columbus-Auburn-Opelika, GA-AL CSA
Gainesville-Lake City, FL CSA
Greensboro–Winston-Salem–High Point..
Hickory-Lenoir-Morganton, NC Metro Area
Knoxville-Morristown-Sevierville, TN ..
Myrtle Beach-Conway, SC-NC CSA
New Orleans-Metairie-Hammond, LA-MS CSA
New York-Newark, NY-NJ-CT-PA CSA
North Port-Sarasota, FL CSA
Portland-Lewiston-South Portland, ME ..
Portland-Vancouver-Salem, OR-WA CSA
Reno-Carson City-Fernley, NV CSA
Savannah-Hinesville-Statesboro, GA CSA
Spokane-Spokane Valley-Coeur d'Alene,..
Springfield, MA Metro Area
Tallahassee, FL Metro Area
Virginia Beach-Norfolk, VA-NC CSA

Table 9: CSAs of the panel, ranked by how amenitied they are, presented by quartile. The ranking methodology is explained in Appendix 4.