Sorting Methods Strategy Scoping Report

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Abstract

1. Introduction

Households “sort” across neighborhoods according to their income, wealth, preferences for public goods and amenities, sociodemographic characteristics, and work location. Workers similarly sort across jobs according to their qualifications and preferences for job attributes. In some contexts, residential choice has a direct impact on work, schooling, and opportunities for social interactions. All of these sorting processes can have important implications for a wide array of socioeconomic outcomes. Over the past decade, advances in the economic modeling of sorting have led to the development of new analytical frameworks that can alter how we think about these processes and evaluate policies designed to affect them. It is our goal to employ these new methods in connection with the unique data sources available through AQMeN to make strides in these dimensions.

Equilibrium sorting models use the properties of housing and labor market equilibria, together with micro-data describing the behavior of economic agents, to estimate structural parameters that characterize those agents’ preferences. Of particular importance is agent heterogeneity (both observed and unobserved). As heterogeneous agents sort, their collective behavior can influence the supply of amenities. These adjustments can be represented as part of the characterization of the equilibria. While they can apply to many different contexts, sorting models have grown largely out of the work of Tiebout (1956), and typically apply to residential decisions and the numerous impacts that those decisions can have. Sorting models can integrate descriptions of how local public goods and amenities are generated, estimate how they affect decision making and, in turn, predict how they will be affected by future policies targeting prices or quantities. Sorting models can furthermore predict how equilibrium prices and quantities will be affected by such policies.

There are numerous dimensions in which individuals make sorting decisions that can have important feedback effects. The attributes of the neighborhoods that a household chooses from may depend upon where its primary earner works, while its preferences for school districts may depend upon the level of education attained by the adult members of the household. As households with different incomes and levels of education decide where to live, they will influence the demographic compositions of neighborhoods. When households vote, their preferences will shape public policies that influence local public goods such as school quality or protected open space. [Bergstrom and Goodman, 1973; Goldstein and Pauly, 1981]

Endogenous amenities create challenges for estimating these models as well as affect market outcomes for private goods, such as housing prices and wage rates. The sorting literature seeks to incorporate the “general equilibrium” feedback effects between economic agents and their environments. Modeling these feedback effects is important for researchers interested in simulating the impacts of a counterfactual policy. In particular, equilibrium feedback can generate welfare impacts equal in magnitude to the policy’s direct effect. For example, Timmins and Murdock (2007) find that the welfare cost of closing a large inland fishery are more than twice as large as when congestion costs are properly estimated and accounted for in policy simulations. With feedback effects, policies can also have unintended consequences. Walsh (2007), for example, finds that increasing the amount of land in protected space can actually lead to less total undeveloped land. Sieg, Smith, Banzhaf and Walsh (2004) show that an improvement in air quality can make people worse off if they had weak preferences for air quality before the improvement and the improvement raises the price of housing at the low end of the air quality distribution. Alternatively, if applied correctly, social interactions can lead to even stronger policy impacts (Dickinson and Pattanayak 2012). It is possible, however, that the goal of policy may be undone by sorting behavior; Depro, Timmins and O’Neil (2014) find that disproportionate exposure of minority groups in Los Angeles to cancer causing air toxics can be largely explained by residential sorting decisions, so that changing rules about the siting of toxic facilities alone is unlikely to solve the “environmental injustice” problem. Finally, feedback effects and social interactions can explain the persistence of segregation (Bayer, Ferreira and MacMillan 2007)

In many ways, the models of sorting processes that we consider are very similar to models of demand for differentiated products, where consumers sort across products in a market (including the outside good of not purchasing). Because of this, many of the techniques used in the sorting literature are derived from models of consumer demand in Industrial Organization (IO). There are, however, important differences between the simple models of consumer demand used in IO and the models we will use here. Analysis is not confined to marginal effects or a partial equilibrium setting. Most important, equilibrium is not determined *only* through prices and quantities. Rather, sorting models can integrate mechanisms describing how non-market goods are generated (e.g., local air pollution is a function of the people who choose to settle in a community and the cars they drive, school quality is a function of the attributes of children and their parents who choose to settle in the same school catchment zone), and determine how they affect decision-making. In turn, they can predict how non-market goods will be affected by future policies targeting prices or quantities. Market equilibria can then depend on feedback effects that occur through non-market transmission routes.

The barriers to recovering the structural parameters underlying a sorting model are formidable. The general equilibrium structure of a sorting model may suggest the need to develop instruments for endogenous amenities, such as open space, crime rates, or school quality. The structure of the sorting problem itself may suggest an instrumental variables strategy (Bayer and Timmins 2007). Other quasi-experimental sources of data variation may also be used to overcome these problems; Bayer, Ferreira, and McMillan (2007) use school catchment zone boundary fixed effects, while Bayer, Keohane and Timmins (2009) use a combination of instrumental variables based on a source-receptor matrix describing pollution dispersion and panel data variation.

Additional challenges arise when sorting models are used to predict general equilibrium responses to counterfactual policies. If a sorting model has multiple equilibria, then the analyst should determine whether the model’s policy-relevant predictions are robust to the choice among equilibria. [[1]](#footnote-1)

Moving costs and other important sources of friction should be included among the constraints on behavior in the model; forward-looking behavior and the role for dynamics should therefore be considered, including expectations about the evolution of future amenities and capital gains from home ownership (Bayer, McMillan, Murphy and Timmins 2011, Bishop and Murphy 2011, Mastromonaco 2013, Ma 2013). Recovering moving costs and preferences in a dynamic context is complicated by the curse of dimensionality, which grows quite rapidly when state spaces are mapped on to geographic diversity. Data has also traditionally been a barrier, as there are few data sets that allow one to track homeowners as they move. That barrier has been reduced by combining name matching algorithms with detailed transactions data (Bayer, McMillan, Murphy and Timmins 2011); the data accessible through AQMeN are promising in this dimension as well. Still, there is a real problem following large numbers of renters and owners, making it nearly impossible to endogenize the role of tenure in the sorting model framework. Maybe there is some hope for this in the use of the Scottish Longitudinal Survey.

2. The Hedonic Framework

In this section, we provide some context for sorting models by describing the hedonic model. Whereas hedonic models treat the sorting process as a “black box”, relying only on the information contained in the equilibrium outcome of the residential sorting process, sorting models get “inside” the box. This both allows the researcher to control for many potential sources of complication (e.g., frictions, forward-looking behavior), but also requires many more modeling assumptions. Going from the hedonic to the soring framework therefore involves important tradeoffs.

The logic underlying sorting models first appeared in the hedonics literature. In particular, sorting models combine the information contained in an equilibrium hedonic price function (Rosen 1974, Epple 1987, Ekeland, Heckman, and Nesheim 2004) with a formal description of the choice processes that underlie market sorting of heterogeneous agents (McFadden 1974, Bresnahan 1987, Berry, Levinsohn and Pakes 1995).

Under mild restrictions on preferences (Bajari and Benkard 2005), the equilibrium price of an individual home *n* in a location *j* can be expressed as a function of the vector of its structural characteristics (), and the vector of amenities associated with the location – i.e., . For the sake of simplicity, we treat that vector as a scalar for the following discussion. While hedonic models date back to Court (1939), Griliches (1971) and Triplett (1969) used hedonic price functions as the basis for price and quality indices for quality differentiated goods. The more recent literature focuses instead on the derivatives of the price function. Rosen (1974) strengthened the economic theory underlying this interpretation of the hedonic model, arguing that the hedonic price function describes an equilibrium outcome. In particular, the hedonic price function represents an equilibrium stratification mirroring that in Tiebout’s (1956) work.[[2]](#footnote-2)



Assuming that households face a continuum of choices, the first order conditions for utility maximization with respect to the local amenity, , are:



(1)



where *b* is a numeraire commodity. The first equality states that households will choose a location that provides them with a level of *X* such that their marginal willingness-to-pay for an additional unit exactly equals its marginal implicit price. Assuming the marginal utility of income is constant, the marginal rate of substitution between *b* and *X* defines the household’s inverse demand curve for *X*, conditional upon all other housing characteristics.



Figure 1: Utility Maximization Along the Hedonic Price Function

Figure 1 shows indifference curves in (*X, P*) space. Higher levels of utility are associated with indifference curves lying further to the southwest. Each household will select the quantity of *X* where its indifference curve is just tangent to the hedonic price function. In equilibrium, will return the household’s marginal willingness to pay for *X* at the particular value chosen by the household. This identifies a single point on that household’s inverse demand curve for *X*.





Figure 2: Marginal Willingness to Pay Curves Associated With Hedonic Sorting

Things are a bit more complicated when the attributes are not described by a continuum as the first order conditions associated with optimal behavior do not hold and are replaced by inequalities (Griffith and Nesheim 2010).

Rosen (1974) proposed a two-step approach for recovering the MWTP function. The first-stage recovers a flexible estimate of the hedonic price function, . That function is used to back out implicit prices for *X*, , which are used as dependent variables in a second-stage regression on *X* and consumer attributes. The result of that second-stage procedure is interpreted as the MWTP function.



There is a long literature identifying problems with the hedonic framework as specified by Rosen (1974). Brown and Rosen (1982), Mendelsohn (1985) note that, with heterogeneous preferences, each data point in the hedonic estimation only identifies one point on each MWTP curve. This is insufficient to recover the entirety of the individual’s demand curve without panel data (e.g., seeing observationally equivalent individuals from multiple markets) or without relying on functional form restrictions.

Epple (1987) and Bartik (1987) demonstrate that measures of the attribute in question will be endogenous in the second-stage regression used to recover MWTP. Moreover, because buyers are non-randomly matched with suppliers as part of the hedonic sorting process, supply-side cost-shifters are not valid candidates for instrumental variables.

Ekeland, Heckman and Nesheim (2004) address both of these problems, noting that the hedonic price function is naturally non-linear; demand curves can be estimated based on idea described in Mendelsohn (1985). They go on to describe a non-parametric estimator that deals with the endogeneity problems described by Epple (1987) and Bartik (1987) by requiring additive separability in utility between individual attributes and amenities. The method is, however, data-intensive and hard to implement.

Bajari and Benkard (2005) and Bishop and Timmins (2011) provide practical alternatives to the approach suggested by Ekeland et al. (2004). In Bajari and Benkard (2005), preferences can be recovered, under strong functional form restrictions, with an inversion procedure using information from a flexibly estimated hedonic price function. By inverting a separate MWTP value for each individual rather than estimating a common MWTP function, the econometric problems described by Epple (1987) and Bartik (1987) are avoided. However, this does come at the expense of requiring strong functional form assumptions about the shape of the MWTP function. Bishop and Timmins (2011), alternatively, use the logic of the sorting model to show how the Epple-Bartik problem can be overcome by looking at the choice of amenities along the hedonic price function rather than at the equilibrium relationship between prices and amenities.

The empirical hedonic literature is broadly divided into two types of papers. First, there are those that focus on identifying the hedonic price function (and use its derivative to find the average marginal willingness to pay in the sample). See, for example, Palmquist, Roka and Vukina (1997), Davis (2004), Greenstone and Gallagher (2008), Linden and Rockoff (2008), Pope (2008), Davis (2011), Zabel and Guignet (2012), Haninger, Ma, and Timmins (2012), Gamper-Rabindran and Timmins (2013), Muehlenbachs, Spiller and Timmins (2014)]. Second, there are papers that seek to recover demand functions for attributes. These include Ekeland, Heckman, and Nesheim (2004); Heckman, Matzkin, and Nesheim (2010); Bajari and Benkard (2005); Bajari and Kahn (2005); and Bishop and Timmins (2011).

As we will see in the following sections, sorting models are particularly useful for dealing with a number of the shortcomings of the hedonic framework. The following list provides some specific examples.

1. Discrete Choice Set – The hedonic model is based on marginal conditions that are only valid when choice sets are continuous. Sorting models typically treat geography, and hence local public goods and amenities, as discrete. We can thus model “holes” in the choice set explicitly.
2. Endogenously Determined Local Attributes – Many of the local amenities in which we are most interested are determined by the sorting process itself. Fortunately, the sorting process often suggests an instrumental variables strategy that can be used to deal with such variables. See Bayer and Timmins (2007) for a description and Timmins and Murdock (2007) for an application of this idea to the measurement of congestion costs.
3. Non-Marginal Changes – Considering large changes in amenities, it becomes necessary to allow homeowners the possibility of re-optimizing. In particular, we might expect to see an entirely new equilibrium price function emerge, and home-buyers would re-sort with respect to it. Hedonic theory does not provide us with any way to solve for an out-of-sample equilibrium price function; by explicitly modeling the sorting processes that lead to equilibrium, sorting models do enable us to predict new residential choice decisions and the equilibrium prices that clear the market. (Walsh 2007; Timmins and Murdock 2007; Tra 2010)
4. Stickiness and Frictions – These are likely to affect the formation of the equilibrium used by hedonics for estimation. By focusing on the sorting process rather than the equilibrium outcome, it is easy to model stickiness in the process that leads to equilibrium. (Bayer, Keohane and Timmins 2009)
5. Moving Costs and Forward-Looking Behavior – Once individuals face moving costs, they will not want to re-optimize in every period and will hence think about the future implications of the current residential decisions; in particular, how will amenities and house values evolve in the future. In sorting models, we can build forward looking expectations directly into the residential decision-making process (Bayer, McMillan, Murphy and Timmins 2011).

3. Sorting Models

In this section, we lay out basic assumptions that underlie the sorting model framework. Many of these assumptions are unrealistic, and relaxing them has been the subject of recent research and will be a focus of our efforts under AQMeN. First, sorting models assume that the amount and character of housing and public goods varies across an urban landscape, and each household selects its preferred bundle of public and private goods given its income and the vector of relative prices. In this sense, sorting models (like hedonic models) follow in the footsteps of Tiebout (1956). Every household pays for its location choice through the price of housing and (depending upon the context) commuting costs and labor market returns.

Second, the sorting literature has been primarily focused on the demand-side of the housing market; land developers are not explicitly represented.[[3]](#footnote-3) Instead, housing supply is usually treated as fixed or represented in a way that allows for simple calibration, such as using a constant elasticity of supply function, perfectly inelastic supply, or perfectly elastic supply.

Third, sorting models typically assume that all households have perfect information about every aspect of the housing market. There have been recent exceptions to this assumption,[[4]](#footnote-4) and we propose one research project below that looks to directly test this assumption. Finally, sorting models typically assume that households do not face constraints in the form of outright discrimination or “red-lining” in their choice of housing unit.

Begin by assuming that the urban landscape consists of *n* = 1, 2, …, N houses that can be divided into communities *j* = 1, 2, …, J. Each house is described by a vector of housing characteristics and amenities. is a vector of structural characteristics that fully describe the private good component of house *n*. *gj* denotes a vector of neighborhood attributes conveyed to every household in community *j*. A household’s utility depends upon the characteristics of housing and amenities at its location and on its consumption of a composite numeraire private good, . Households, indexed by *i* = 1, 2, …, I are allowed to differ in observed demographic characterics () and unobservable features of their preferences (). In the simplest model, a household may contain many different members with different attributes and preferences, but is portrayed as a single indivisible agent. Relaxing that assumption is an area of active research and may be something that we consider [see, for example, Gemici (2008)].



Household *i* is assumed to solve the following utility maximization problem:

(2)



choosing over location *j* and, by virtue of i's budget constraint, numeraire consumption . is an index derived from the vector of housing attributes that describes the quantity of housing services being consumed. represents the after-tax annual expenditures on a unit of housing services in community *j*. This is typically found by running a regression of the form:



(3)



(4)



represents the household’s annual income, which can vary with location choice because of local employment options and commuting costs.



This simple formulation of the problem implicitly assumes away three potential sources of “friction”. Households are assumed (i) to have full information (i.e., every household knows the joint distribution of *h*, *g* and *P*; is, however, typically assumed to be private information), (ii) to be freely mobile (i.e., households are free to move within the geographic region defined as the choice set and face no physical or psychological costs from moving), and (iii) to make location choices in a discrimination-free environment (i.e., every household faces the same schedule of housing prices). Some of the recent advances in this literature have focused on relaxing these assumptions. For example, Bayer, Keohane and Timmins (2009) estimate an inter-city migration model with simple moving costs based on distance from birthplace. Bayer, MacMillan, Murphy and Timmins (2011) construct an intra-city model of residential mobility allowing for financial and psychological costs of moving. These moving costs imply that homebuyers will not want to re-optimize every period, and will therefore be forward looking with respect to the future evolution of neighborhood amenities and home value.



Under these simple assumptions, equilibrium is achieved when every household occupies its utility-maximizing location and no household wants to move given housing prices, housing characteristics, wages, tax rates, and amenity levels.

3.1 Incorporating Social Interactions

Sorting models become particularly useful when modeling preferences for local public goods and amenities that are determined endogenously by the sorting process itself. In an early application, de Bartolome (1990) added social interactions to a model of residential choice, where two types of households (low skill and high skill) sort across two communities according to differentiated preferences for school quality, which increases in expenditures and household skill. de Bartolome (1990) finds that there is potential for many equilibria and, importantly, some of those equilibria are inefficient. With just two locations, it is a simple matter to characterize these multiple equilibria – we may have strict segregation according to skill (although even this allows for two possible equilibria with each skill group having the potential to locate in each community). We may, however, have an “integrated” equilibrium in which both communities contain both types of households.

Nechyba (1999) extends de Bartolome’s (1990) model to I household types sorting among J school districts, where each district contains multiple housing types of varying quality. He uses the model to study the effect of a private school voucher program and finds that it reduces inequality between rich and poor districts.

Durlauf (1996) uses social interactions to model the potential for “poverty traps”. He demonstrates that short run stratification can have long-term consequences for inequality and growth. Parents who have the misfortune to be born into a poor community may be unable to raise school quality enough for their children to obtain higher paying jobs. One potential solution to this poverty trap is to equalize expenditures on education across districts. The net benefits hinge on an intergenerational tradeoff between the short run cost of constraining expenditures on education and the long-run benefit of reducing inefficiency from stratification.

Sethi and Somathathan (2004) model sorting with social interactions, finding that households prefer integrated communities to segregated ones, but if forced to choose between two racially segregated communities, would prefer to live in the one occupied by their own race. Their model relies on a “single crossing” property (see below) – all else equal, households are thus stratified by income. To illustrate how the two effects combine to sustain segregation, consider an initial equilibrium in which households are effectively stratified by race due to a large white-black income gap, but would prefer to be integrated. As the income gap narrows, a rich black household living in the predominantly black community has less of an incentive to move to the predominantly white community because the white community has become less affluent in relative terms.

3.2 Vertical Sorting Models

The first iterations of sorting models described the equilibrium process by way of a number of additional assumptions. Ellickson (1971) assumed that the provision of public goods in community *j* could be represented by a 1-dimensional index, . Second, he assumed that households have homogenous preferences () and differ by only one observed attribute, income. Finally, he imposed the restriction that indifference curves in the space are strictly increasing in income. These assumptions support a sorting equilibrium in which households are perfectly stratified across communities by income. Figure 3 illustrates this idea with a two-community model. Household *b*, with income *yb*, is exactly indifferent between the two communities. Any household with income less than that of household *b* will choose community #1, while any household with income greater than that of household *b* will choose community #2.





Figure 3: Single-Crossing Property

Using the restrictions from Ellickson (1971), Westoff (1977) proved that a sorting equilibrium exists in a model where households in each community vote to determine public good provision and community-specific tax rates. Epple, Filamon and Romer (1984) extend Westoff’s model to include a housing market that must clear within each community.

While these models formalized Tiebout’s theory, they unfortunately did a poor job of describing data from the real world. The reason for this was simply because, after ordering households by the quality of their public goods provision, , it was not typically the case that communities were actually partitioned by income. In reality, community-specific income distributions overlap considerably. Epple and Platt (1998) therefore extended the vertical modeling structure to accommodate this feature of the data by allowing households to have heterogeneous preferences for public goods; household *i*’s relative preference for public goods is described by . Equilibrium is then characterized by a generalized single-crossing restriction. In particular, an “indirect indifference curve” in space is assumed to be monotonically increasing in *y* conditional upon and in conditional upon *y*.



The single crossing property now implies three different equilibrium results that characterize sorting by each household type: (i) boundary indifference, (ii) stratification, and (iii) increasing bundles. Organizing communities by their indices of public good provision, , boundary indifference requires a household on the border between two communities in space to be indifferent between those two communities.





Increasing bundles requires that for any two communities in the ordering (*j*, *j*+1), the following must be true:

(5)



i.e., the ranking of communities by public goods must match their ranking by price.

Finally, the stratification property requires that households are stratified across the J ordered locations by and by .



(6)



Equilibrium with preference heterogeneity can therefore be reconciled with overlapping income distributions across locations.

Proof of existence of an equilibrium can be obtained simply by computing the vector of prices and public goods such that no household could increase its utility by moving. Proving uniqueness of that equilibrium is more difficult – no such proof exists for the model allowing for preference heterogeneity. This becomes an issue when the goal is to use the model to predict a counterfactual equilibrium subject to some policy.

Epple and Sieg (1999) were the first to empirically implement the vertical model. They begin with a CES indirect utility function:

(7)



where is an index of local public goods associate with location *j*. represents consumer *i*’s preference for public goods relative to private consumption. is the price of a unit of housing services in location *j* (). represents individual *i*’s income. represents the joint distribution of income and public good preference. The model is identified by parametric and distributional assumptions:



(8)



where are observable attributes of location *j* and is an unobserved (by the econometrician) attribute. Importantly, in the vertical sorting framework all agents are required to similarly value the different components of *g* as the make-up of the index . Households agree on the ranking of communities with respect to , although they may have different relative preferences for and private consumption. Roy’s identity applied to indirect utility yields the demand for housing services:



(9)



where and indicate the price and income elasticities of demand for housing, respectively.



Estimation proceeds by (i) guessing at parameter values, (ii) calculating the values of that place the correct share of population in each location, given the assumed distribution of based on guessed parameters , (iii) predicting income and housing expenditure distributions in each location. Identification is achieved by matching within-community distributions of income and housing expenditure to observed data. (iv) The vector is then regressed on , treating as an orthogonal error term. Importantly, this assumes , which rules out local attributes that are determined by the sorting process.[[5]](#footnote-5)



Epple and Sieg (1999) describe a strategy for IV based on increasing bundles and income rank. Intuitively, , , and will follow the same ranking across communities. Their instrumenting strategy uses functions of the income rank to instrument for . Since income rank is a function of the model, which means a function of , the underlying assumption is that is not significant enough to affect the income rank.[[6]](#footnote-6)



The vertical sorting framework proves to be particularly adept at modeling local public goods that are determined endogenously by majority vote. Epple, Filamon and Romer (1993) describe how a voting equilibrium can be incorporated into the vertical framework that allows public goods to be determined by local majority. Calabrese et al. (2006) extend this model to allow for peer effects and majority rule voting on property taxes used to finance local public goods.

3.3 The Limitations of the Vertical Model

The primary problem with the vertical sorting framework is that it requires all households to agree on the relative rankings of many locations with potentially many different values of many public goods. This is because the vertical model treats the public good as a single-dimensional index, rather than allowing heterogeneous agents to have different preferences for different components of that index. This requires, for example, that parents of school-aged children and the elderly agree on the ranking of two communities – community (A) with a high-quality schools and moderate air pollution, and community (B) with low-quality schools and low levels of air pollution. We might expect parents of school-aged children to value community (A) over community (B), although the result may flip for the elderly if they place very little weight on school quality. An alternative modeling approach, the horizontal sorting model framework, relaxes this assumption by allowing each type of household (indeed each individual household) to have different relative values for different public goods. Of course, this comes with a different set of assumptions and modeling restrictions.

3.4 Horizontal Sorting Models

The horizontal framework importantly relaxes the assumption that all households must similarly rank all communities according to their combined public goods. Households can differ in their relative preferences for different local attributes. Indirect utility is specified as:

(10)



where the vector of preference parameters can be different for every individual.[[7]](#footnote-7) is an idiosyncratic error term (i.e., it is unique to every individual and choice alternative). Assuming Type I Extreme Value yields a closed form for the probability that individual *i* will choose alternative *j.*



(11)



Berry, Levinsohn, and Pakes (1995), a paper from the industrial organization literature that focuses on the demand for automobiles, proposes a convenient procedure that can be used for estimating the parameters of this model. Writing individual preference parameters as the sum of a baseline coefficient, a vector of observable individual attributes and a vector of individual taste shocks :



(12)



we can separate out the baseline utility associated with each location *j* :



(13)



(14)



Berry (1994) establishes a contraction mapping that allows the researcher to solve for the values of that equate predicted shares to actual shares given a guess at model parameters. Estimation proceeds by finding the parameter values that either maximize the likelihood of observed individual decisions (microdata), or match model predictions to the conditional distributions of individual attributes (e.g., the mean value of conditional upon choosing *j*).



After recovering , the values of and can be recovered by linear estimation:



(15)



Because this is a linear regression equation, it is straightforward to control for (i) spatial correlation in , (ii) endogeneity of (i.e., ) and (iii) endogeneity of (i.e., ).



Bayer and Timmins (2007) describe an instrumental variables approach that can be implemented when can be written as a function of population shares (i.e., a direct function of shares could indicate congestion or agglomeration effects; using a function of type-specific shares could control for crime, school quality, and other local attributes that could depend upon endogenously determined population mix). The intuition behind that strategy is to derive predicted shares based on only exogenous determinants of sorting– if exogenous determinants are important, they will be correlated with observed shares, but uncorrelated with by construction. The level of the endogenous attribute will therefore be a function of the exogenous attributes of every other location – if there is sufficient variation in these exogenous attributes, the instrumental variables will have power.



When measures school quality, Bayer, Ferreira and MacMillan (2007) use school boundary fixed effects as in Black (1999) to control for unobserved local attributes in the second-stage decomposition of . Other applications that utilize this modeling framework with other approaches to identification include Tra (2010), Klaiber and Phaneuf (2010), Schmidheiny (2006), Timmins (2007), Takeuchi, Cropper and Bento (2008), O’Hara (2013).



3.5 PE v. GE Welfare Analysis

Partial equilibrium willingness to pay (measured by compensating variation in income) is defined by:

(16)



i.e., everything else besides the policy variable is held fixed as individuals are not permitted to reoptimize over their residential choices. This is essentially the assumption underlying the hedonic framework. This measure could therefore be calculated either from a structural (two-stage) hedonic estimation or from an estimated indirect utility function from a sorting model.



The general equilibrium compensating variation welfare measure is given instead by:

(17)



In particular, individuals are permitted to re-sort after the changes in (i.e., from choice *j* to choice *k*), and equilibrium prices may adjust as well. Moreover, if individuals sort across labor markets, income could also change to reflect the new location choice *k* (i.e., could also be subscripted by *j* or *k* to reflect the influence of spatial variation in labor opportunities or commuting costs).



This raises questions about how one should calculate a new equilibrium. (1) We need a model of (or at least an assumption about) housing supply. To what extent does supply adjust in response to changes in housing demand and what does this imply for prices? How does the answer to this question vary across the short- and long-run? (2) We need a way to model changes in population into and out of the system (i.e., immigration or emigration). (3) We need to consider who wins and who loses when prices change. Most sorting models treat everyone as a renter. Some models focused on dynamics (e.g., Bayer, MacMillan, Murphy and Timmins 2013; Epple, Romano and Sieg 2012) only use data describing owners. (4) How should we treat frictions? (5) Should we worry about transitional dynamics? This can make the way in which moving costs are treated very important (the question becomes less important if we are mainly worried about long-run dynamics). (6) Multiple equilibria may be important. The most interesting models have the potential to generate many combinations of equilibrium values. We need some sort of selection rule. Bayer and Timmins (2005) provide conditions under which we can expect uniqueness in a class of horizontal sorting models – in particular, when we have a congestive social interaction effect. In the absence of such simplifications, are there ways to make conclusions about the effect of policy that are robust to decisions about equilibrium selection rules (i.e., which apply to multiple equilibria outcomes)? What if we rule out certain equilibria (e.g., Pareto inefficient)?

4. Incorporating Frictions

There has been a recent focus in the sorting literature on accounting for moving costs, information imperfections, and other sources of friction that could affect the formation of hedonic equilibrium, but which cannot be dealt with in the simple hedonic framework.

Bayer, Keohane and Timmins (2009) demonstrate in a simple horizontal framework the important role that long-run stickiness can have on hedonic estimates. Their approach takes the simplest possible approach to the incorporation of stickiness in an inter-city sorting framework, allowing individuals to have idiosyncratic preferences for their birth locations. This form of moving cost helps explain why they see a majority of adults choosing to live in their census division of birth, despite seemingly attractive labor and housing market opportunities elsewhere. As many U.S. adults in 1990-2000 were born in polluted parts of the country (e.g., the northeast and rust-belt) prior to the great migration waves to the south and southwest, they find that failing to control for a birth location preference will lead one to severely understate willingness to pay to avoid particulate matter air pollution.

More recent work has sought to introduce moving costs in various forms. In the following two subsections, we describe two applications in detail that will be relevant for our AQMeN research. The first illustrates a strategy for modeling sorting in the horizontal context when one is constrained to use aggregate data on population flows. The second shows how moving costs, which logically suggest forward looking behavior on the part of home buyers, can be incorporated into a hedonic modeling framework by using elements from the sorting literature.

4.1 Simple Moving Costs with Aggregate Data

In this section, we describe an approach to modeling sorting decisions that can be implemented with readily available aggregate data.[[8]](#footnote-8) The difficulty with using such data comes in determining how to recover the parameters of a model of individual behavior using only data on aggregate population flows. Because of these data limitations, the model relies on more assumptions than would a model that uses individual data.

In order to motivate the aggregate data modeling strategy, we begin with a series of simple examples that illustrate how easy it is to draw incorrect conclusions from aggregate data. Consider a city with just three locations (*j* = 1, 2, 3) observed in each of two time periods (*t* = A, B). We use  to measure the population in location *j* in period *t*.  is used to denote the share of individuals in location *k* in period A who choose to reside in location *j* in period B. We refer to *S* as the “transition” matrix that describes population flows between periods *A* and *B*. The market dynamics associated with this collection of locations are therefore described by the following system of equations:

 (18)

A simple approach to the description of population dynamics might consider the change in the population of a particular population group in each location *j* (i.e., ) and compares it to the initial exposure to some neighborhood attribute (). is typically taken as evidence that members of the group in question “come to the attribute”. Unfortunately, the interpretation is not that simple. The *individual* behavior of “coming to” or “fleeing from” the attribute is instead described by the elements of the matrix  and the way in which  co-varies with the change in exposure associated with the move from *k* to *j* . The elements of  provide a true measure of how the change in exposure associated with a move affects the tendency of individuals to make that move.



The empirical challenge is that the change in population vectors over time does not identify . Recognizing that

 (19)

equations (18) and (19) constitute a system of six equations with nine unknown values of . The system is, therefore, under-identified. Put differently, without additional structure, there is not a unique  matrix that can explain the observed changes in aggregate populations. We expand upon this idea with a series of numerical examples. In each, we consider a different  matrix, but maintain the same distribution of attribute levels: , , . In terms of timing, we model movements between periods *A* and *B* assuming that individuals observe the attribute levels in period *A*. Between periods *B* and *C,* individuals might move again after realizing updated attribute values, .



In the first two numerical examples,  is constructed to yield the same changes to population in each location:  As a result, both examples are characterized by the same aggregate population dynamics. Although a simple analysis would interpret the population dynamics as “coming to the attribute” (i.e., population falls in the low-attribute community and rises in the high-attribute community), a regression of  on  and an intercept shows that the true individual market dynamics in each example are different. The estimated parameter on  in example #1, -0.8805, reflects “fleeing the attribute” (i.e., an increase in the attribute makes a particular move less likely) while the estimated parameter in example #2, 3.409, reflects “coming to the attribute” (i.e., an increase in the attribute makes the move more likely). P-values are reported in brackets.[[9]](#footnote-9)

Example #1:



*Slope coefficient = - 0.8805 [0.666] (Coming to the Nuisance)*

Example #2:



*Slope coefficient = 3.409 [0.276] (Fleeing the Nuisance)*

Our third numerical example shows that sorting in response to neighborhood attributes can still occur at the individual level even when the aggregate distribution does not change. In Example #3, the aggregate population distribution remains constant between periods 1 and 2; however, the correlation between  and  reveals residential mobility consistent with “fleeing the attribute” (an estimated coefficient of -7.50).

Example #3: No Change in Aggregate Population Distribution



*Slope coefficient = - 7.50 [0.061] (Coming to the Nuisance)*

All three examples make clear that aggregate population dynamics alone are not able to distinguish the change in circumstances individuals face when moving. This is particularly important in light of the fact that policy analysis is frequently interested in precisely the question of how individual circumstances change in response to a policy.

The solution to this problem is to use modeling strategy to draw micro implications from aggregate data. To better understand the neighborhood dynamics underlying the observed changes in aggregate demographics, we build on the model described above, placing some structure on  (the share of individuals of a particular group in tract *k* who choose to move to tract *j*) so that we can identify the role that neighborhood attributes play in individual residential decisions. Equations (18) and (19) represented a system of six equations with nine unknown ’s, leading to an identification problem. By parameterizing  as a function of location attributes, we overcome the identification problem. Start with the predicted population in neighborhood *j* in period *B*:

 (20)

Next, specify the mean utility from living in location *k* () as a function of observable attributes of that location (), attributes that are unobserved by the econometrician (), and a vector of parameters ():

 (21)

The utility an individual *i* receives from living in location *k* is given by:

 (22)

where  refers to the idiosyncratic utility specific to that individual and location. The change in utility an individual *i* currently living in location *k* receives from *moving to* location *j* is therefore given by:

 (23)

where  is a direct measure of moving costs. If , , meaning that the change in utility from staying in one’s current location is zero.

If is distributed i.i.d. Type I extreme value, then the share of individuals in location *k* who find it optimal to move to location *j* is given by the familiar logit functional form:

 (24)

Similarly, the share of individuals in location *k* who would find it optimal to remain in that location is given by:

 (25)

The model of migration becomes complicated when we recognize that many of the observed changes in the aggregate distribution of population may actually reflect broader migration patterns into and out of the “system” being considered. The problem of the “open system” is common across papers looking for evidence of residential mobility, and it exacerbates the problem of not knowing all individuals’ starting locations and ending destinations. It arises whenever the researcher considers a subset of locations, allowing movements into and out of that subset.

In Depro, Timmins, and O’Neil (2014), we consider movements within L.A. County census tracts (*k* = 1, 2, …, N) and a single “catch-all” location (*k* = N+1) that captures all other locations. We discuss below why this simplification and, in particular, the number of individuals assumed to be in the catch-all location, is innocuous when it comes to identification and estimation. Moreover, in that application we use data from the 2000 decennial census to define period *A*, and data from the 2005-2009 5-year American Community Survey sample to define period *B*. Both data sets take 5% samples of the total population. In the description of the estimation that follows, we will refer to the two periods as 2000 and 2007.

Estimation of the aggregate data model is carried out in two stages. We begin by finding the vector of  and  that best fit the data. Of course, without additional information, this system contains N+2 unknowns and only N+1 equations describing the mapping of populations from 2000 to 2007 in each location. It is therefore still unidentified. We do have access, however, to an additional piece of information that solves this problem. In particular, we observe the share of households in each race subgroup in L.A. County that *do not move* between 2000 and 2007.[[10]](#footnote-10) These percentages, described in Table 4, provide us with an additional equation that must hold for each race group *R*:

 (26)

Practically, solving for  and is made simple by noting that, if we divide both sides of equation (20) by , we get:

 (27)

where .[[11]](#footnote-11) Conveniently, given a guess at , equation (27) represents a contraction mapping in . We can solve for those values by first taking a guess  subject to a suitable normalization.[[12]](#footnote-12) We then use that guess in conjunction with the observed population shares in 2000 () to calculate predicted population shares in 2007 () . We then update the  guess according to the following rule (Berry 1994):

 (28)

The vector  is used to generate predictions of , which in turn are used to generate a new vector . This process is repeated until the difference between  . With the converged values of  and the guess at , we then calculate the predicted percentage of the 2007 population who did not move from their tract in 2000, and check to see how that value compares with  for the appropriate racial group. We use a bisection method to search over values of  that equate predicted  to actual , solving for the values of  at each step.

The methodology described above assumes a positive population share () in each location in each period. In our EJ application, we apply this procedure to different racial groups. Using a high-resolution definition of geography (e.g., census tracts), it is possible to observe tracts containing no members of a particular group. This is, in fact, the case in L.A. County, where 3.3% of tracts contain no whites, 14.9% contain no blacks, 10.0% contain no Asians, and 0.1% contain no Hispanics. This creates a practical difficulty, as equation (28) is not defined for a particular value of *j* if .

We deal with this problem by adding a “patch” – i.e., a small positive artificial population  (e.g.,  to each location; all locations will then have positive shares and the procedure described above will be computationally feasible. However, the value of  associated with zero-share locations will become increasingly negative as the value of  becomes smaller and smaller as . This would create a problem using a simple least-squares regression technique to decompose .[[13]](#footnote-13) Consider a linear specification of equation (21):



 (29)

In particular, OLS estimates of  will vary with the choice of . However, if fewer than half of all locations have positive population shares, we can decompose  into its component parts using median regression. Median regression is a particular case of quantile regression (Koenker 2005) that is robust to the choice of . With fewer than half of the locations having zero true population shares for any race group, median regression results are invariant to the choice of . Depro, Timmins and O’Neil (2014) demonstrate that, even with significant population segregation, median regression estimates are invariant to the choice of , while OLS estimates are highly sensitive.



Depro, Timmins and O’Neil (2014) consider the median regression for each race group separately. Note that, because each race group’s  is normalized so that its mean value is zero, parameter estimates are not directly comparable across race groups; however, the relative tradeoffs individuals make between tract attributes can be compared. In particular, it is a simple matter to measure the tradeoffs individuals make between neighborhood attributes and other consumption. This can be found by simply dividing the coefficient on the neighborhood attribute by, , the marginal utility of income.

4.2 Moving Costs and Forward Looking Behavior in the Hedonic Framework (Bishop and Murphy, 2011)

Traditional hedonic models treat housing purchase decisions in a static framework. Home buyers are not forward looking with respect to the evolution of amenities. If homeowners face moving costs, however, then it is costly to re-optimize and home buyers account for the fact that, whatever house they buy, they will be stuck with it for a while. The modeling approach adopted in this paper is relatively simple in that it only allows for “psychological” moving costs (i.e., direct disutility associated with moving) but does not consider the financial costs associated with paying a realtor (typically some percentage of the house’s value). Consequently, it also does not consider the wealth impacts of home ownership and the possibility for capital gains/losses. It is, however, easy to implement. The focus is on allowing consumers to have forward looking expectations with respect to evolving neighborhood attributes.

Accounting for forward looking consumers can be important. A model that ignores this feature of consumer behavior will understate the flow value associated with amenities that change over time, while it will overstate the flow value associated with amenities that are persistent.

The model begins with the standard Rosen model framework:

(30)



* amenities associated with a home occupied by household *i* in period *t*



* observable attributes of household *i* in period *t*



* unobservable determinants of household *i*’s preferences in period *t*



* hedonic price function (all house prices are converted to rent



This implies the following first order condition

(31)



In an initial stage, we estimate . In the second stage, those estimates are used to recover the parameters of utility:



(32)



The goal of the Bishop-Murphy approach is to preserve this basic framework while including moving costs and forward-looking behavior.

Consider household flow utilities that are choice specific (in particular, specific to whether or not the household moves in the period in question):

(Non-Movers) (33)



(Movers) (34)



* Endowment level of X



* Optimized level of X chosen by movers



* moving costs



We could use these choice-specific flow utilities to define the value function (i.e., the expected present discounted value of the future stream of utility given optimizing behavior):

(35)



Given that the household behaves optimally in the future regardless of what it does today, we can define choice-specific value functions iteratively:

(36)



(37)



where measures the flow utility associated with the move to the optimal The household will decide to move this period if:



(38)



Assume that i.i.d. Type I Extreme value with scale parameter . We could use this inequality to form a logit estimating equation based on observed move/stay decisions. But we would need to know the form of and . The state space is prohibitively large so that this cannot be solved explicitly.



Instead, begin we begin the estimation by focusing on the continuous choice made by movers.

Assumption: This period’s choice of only affects next period’s endowment but does not affect the transition of any other state variables.



This rules out wealth depending upon the value of the house; we need the more complicated Bayer, McMillan, Murphy and Timmins (2011) model to include those. The important implication of this assumption is that my choice of where to live today only affects my endowment next period. If I choose to move next period, that value will have no impact on my future utility. As such



(39)



This implication turns out to be useful. In particular, we can expand the inclusive value in the choice-specific value function under the logit assumption:

(40)



where

(41)



(42)



So, the inclusive value term will be given by:

(43)



Noting that moving costs are not a function of , setting yields:



(44)



The probability of moving at different values of the state space, , can be calculated directly from the data, and the derivative with respect to ,, can be recovered as well. Combined with an estimate of , we can now recover the parameters of the flow utility equation by estimating:



(45)



The standard hedonic model ignores the future value term,



5. Data (THIS SECTION NEEDS A LOT OF WORK – WE MAY NEED SOME HELP HERE FROM GWILYM AND JON)

Applications of the hedonic framework or sorting models will be based on the rich pool of data for Scotland and specifically Glasgow that we will develop and connect in this AQMeN strand. We will now discuss the data sources in more detail and also describe ways to connect them.

Land Registry (England) – no information about buyer or seller; a little bit about the house.

*Registers of Scotland* – names of buyers and sellers (tracking). No information about house.

Are we just going to be using house fixed effects?

*Strathclyde Police Data*

* Vandalism (broken windows?) – gentrification induced by cleanup of vandalism effects. Caetano et al. Feedback effects?
* Gang activities – Estate generational gangs. How often do the police get called for it; gang territory maps (intelligence data – can we get that?). Concentrated in social housing (no house transactions)

*GP Registration Data*

A way to get aggregate population flows between areal units.

*Scottish Neighborhood Statistics*

At the datazone level.

6. Conclusions: Applications and Proposed Models

In this final section, we conclude our review with a brief description of the projects that we intend to pursue based on the hedonic and sorting model literature discussed above.

*(1) Aggregate Data Sorting Behavior (Draft Target Date 5.30.13)*

Work on this project, which will parallel that described in Section 4.1, can begin immediately as it does not rely on having access to specialized micro data. Rather, this project can be implemented using publicly available information (in particular, exploiting Scottish neighborhood statistics at the datazone level). The idea will be to look at environmental improvements and measure valuations based on sorting behavior, and use the model to predict movements in response to policy. An important implication for our AQMeN strand will be on how these movements increase or decrease segregation. A number of specific questions include: (i) Environment – data are available at the datazone level, including information on brownfield contamination levels and other measures of air pollution. Our plan is to obtain these data from the Scottish EPA along with information about specific land uses (e.g., waste storage). (ii) Segregation – how do people segregate on occupation classification; how does cleaning up an environmental problem lead to a reduction in segregation? In order to answer this question, we will need to incorporate feedback effects. This project will rely heavily on publicly available data at the datazone level.

Extensions: We may be able to enhance identification by using GP registration data to measure probabilities of movements between geographic units. These data can be taken to predictions of the model, leading to overidentification, which creates a great opportunity for model verification. (out of sample model verification). What are the segmentation questions?

*(2) Micro Data Test of Aggregate Data Model*

This project exploits the unique access to linked micro data over time (e.g., from the Registers of Scotland by matching names) to determine how people in different groups actually did move. The data allow us to directly test the implications of the model in (1). We only need to follow individuals when they move and determine whether, for instance, the poor tend to move towards or away from pollution. In particular, when confronted with a disamenity, we are interested in the following sequence of questions: Do we see the affluent members leaving first? Whom are their houses re-filled by? What does this do to endogenous local amenities? Does this create feedback effects? The rich information in matched ROS data will provide a unique opportunity to answer these questions directly, and to test the modeling structure described in (1).

(3) Windfarms (Draft Target Date 3.30.13)

Work on this project will use information on property values to determine the non-marketed costs to nearby residents of wind turbines. This hedonic exercise will have policy implications as wind power is projected to become an important component of Britain’s renewable energy portfolio. Wind farms may affect property values in different ways. We will distinguish two types of effects. First, effects from one or more wind turbines being in view of a property and second, effects from wind turbine noise (with the latter varying with the size of a wind farm). We capture the relationship between the visibility of wind turbines and house prices using difference-in-difference (DD) estimations that compare property values in the view sight of at least one wind turbine (S) before and after the establishment of the turbine to places that cannot be seen (NS) but are located close by. Since we compare properties within a small geographic range, unobserved and potentially confounding neighborhood attributes should not differ much. Moreover, we would expect the distribution of visual obstructions preventing view of the turbine to be random with respect to other neighborhood unobservables. Our DD approach then compares changes in property values for houses where a wind turbine is within and out of view respectively.

To disentangle noise effects from view effects, we can extend the DD estimation to a DDD estimation. The DDD allows us to account for view-area specific changes in property values and noise-area specific changes in property values when we measure the additional change in property values of houses that are exposed to noise and view sight effects. Comparing the coefficients of houses that (i) can only see, (ii) can only hear, or (iii) can see and hear the wind turbine then allows us to separate the effects.

To define areas that are exposed to the noise or the view of a wind mill, we employ ArcGIS viewshed technology. Compared to existing research on the effect of wind turbines on house price values (e.g. Gibbons 2013), we will not consider the existence of a wind farm as treatment but seek to assess the effect of every single wind turbine in a wind farm. Using view sheds calculated from an individual turbine instead of the centroid of the wind farm will give precise information on exposure and provides a way to assess differences in the level of exposure (i.e., being exposed to one or more wind turbines).

*(4) Neighborhood Effects*

Linked population data from the Scottish Longitudinal Survey should allow us to follow individuals over long time-horizons and geographical space. With these data, we will look at how conditions in childhood (e.g., health, exposure to crime, school quality, neighbor sociodemographics) affect outcomes later in life (e.g., labor market, crime/drug use, neighborhood choice). How do outcomes vary depending upon whether one grows up in a high crime vs. low crime neighborhood? How does the race or religion of ones neighbors as a child affect sorting decisions as an adult? How does childhood pollution exposure affect health and labor market outcomes as an adult? Understanding how all of these outcomes affect sorting decisions has particular relevance in the study of poverty traps (see below).

There is a growing literature on neighborhood effects to consider. Important papers in this literature to consider are Lalive and Cattaeno (2009), Bobonis and Finan (2009), Bayer, Ross and Topa (2008), Gibbons, Silva and Weinhardt (2013),[[14]](#footnote-14) and a survey article by Galster et al. (2008).

Completion of this project will require access to SLS and geographic histories based on GP data. Our understanding is that access to these data is dependent on Chris Dibbins. In addition, we will require information about school performance and socioeconomic background. There may also be scope for incorporating information on criminal activity. In particular, we will seek out what information is available in Datazone units for 1991 and 2001 in the SNS.

An extension of this research will analyze preference formation. In particular, can we see how circumstances early in life affect preferences later in life (e.g., for living in a segregated community? ) This would require that we get geographically coded SLS data to build a sorting model of neighborhood choice that allows for preferences for neighbor attributes, and for preference heterogeneity to depend upon early-life situations.

*(5) Poverty Traps*

This project will build upon the neighborhood effects analysis and merge it with a sorting framework. This combination allows us to examine how neighborhood effects determine where people live and their (in)ability to escape poverty. Specifically, how does living in a poverty-stricken neighborhood as a child affect the likelihood that this will be the case as an adult, all else equal? What are the determinants of persistent poverty (Durlauf 1996)?

*(6) Crime*

Crime evolves rapidly and it is therefore a local disamenity with potentially important dynamic consequences. We propose to look at how dynamics and forward looking expectations about crime affect valuation. In doing so, it is straightforward to apply the techniques of Bishop and Murphy (2012) described in Section 4.2. We may also consider using techniques described by Bayer, McMillan, Murphy and Timmins (2011), which allow for consideration of wealth effects and incentives associated with housing appreciation that may accompany neighborhood gentrification.

The research plan on crime will start with a descriptive paper about crime trajectories using crime data for the Strathclyde region. This provides motivation and documents the underlying trends before proceeding to the dynamic analysis. We also have an interest in pursuing work related to gang activity and the value of violence reduction policies. A challenge in that application is that gang activity tends to occur in social housing areas, where there are no housing market prices.

*(7) School Performance*

There has been work before using sorting models to value school quality and feedback effects, but access to better data than that which has been used previously would make an important contribution. Data to do this could be very good in Scotland, but may be hard to get. We look to set up research questions with the Education Strand (Christina Ianelli)

* Role of religion and special catchment areas
* Lotteries and expectations about school quality (can we access placement request data?)
* Feedback effects of school quality/peer effects in a sorting framework.
* Students can attend good school by living in neighborhood, but can keep enrollment when they move. Does this policy lead to more/less segregation (i.e., when ability to attend good school is separated from geographic location)?
* Schooling and gentrification.

We will explore a number of possible data alternatives: SLS, Sample of Anonymous Records (SARS) – a 1% sample

*(8) Contagion Effect in “Right to Buy”*

Poor were given the option to buy their social housing units. Does one household’s purchase of its social housing unit affect how many of their neighbors choose to buy as well? When one’s neighbors buy their units, do we observe that expectations for future neighborhood housing value improve. The idea is that home-owner-neighbors will take better care of their property and expectations of future house price rises increase, so other individuals are more willing to buy as well. A direct policy implication is that home ownership may lead to better neighborhood effects and avoid poverty trap impacts. The opposite could also be true – worse neighborhood effects in places where no one buys, house quality deteriorates, and fewer households choose to buy in the future.

We would need develop an empirical strategy to identify contagion effects. First people who buy have access to money, but those who come later would be partially driven by the contagion effects. Timing may be enough to achieve identification. We could consider alternative approaches to disentangling these competing effects.

This research may be possible because ROS tells us if people bought their house from the local authority (City of Glasgow or Glasgow City Council). Question – is the big wave of social housing purchases post-1990 covered by our data?

We will explore alternative data sets (possibility of attaching spatial variables to the BHPS?).

*(9) Seller Motivation and Its Role in Hedonic Modeling*

Use Zoopla in combination with ROS to determine if those who are moving a long distance (motivated sellers?) are more likely to lower their price over time. We typically have data on either how prices behave after a house goes on the market or where people move to, but not typically both. We could run a hedonic estimation for the value of neighborhood amenities (e.g., school quality, crime, pollution measures) and try alternative variables that could control for this source of bias.

*(10) Informed v. Uninformed Buyers in Hedonics*

Do those buying from a distance make improper decisions with respect to how amenities are priced? We can estimate the hedonic price function using only local purchasers and then see if the out-of-town buyers make different tradeoffs. Ideally, we would carry out this exercise in a combination with data on crime. Crime is highly localized. It would be particularly interesting to see if information about crime becomes available to local residents – we could then look before and after the information release, and compare residential location decisions of local and long-distance buyers.

* Localized online knowledge
* Peace Index – describes crime levels at the district level. Everyone should be able to get access to this.

Ideally, digitize buyer attributes and add to ROS (this would allow us to combine information about income, mortgage, etc…). This would allow us to control for income. Is there some way to get it scanned and digitized?

Can we buy more recent ROS data? We can match the RMS data on the house that got bought and that would give us some individual attributes.

GSPC (Glasgow data) – This would provide us with access to rich data on property attributes. We’d only be looking at people moving into Glasgow. Agent ID’s? That would let us look for agents who specialize in out-of-town buyers. We could see if people coming from outside bargain differently. Use neighborhood fixed effects and look to see if locals make better decisions in sorting within the neighborhood.

(*11) Transaction Date Bias*

Use Zoopla to determine if there is a bias from using the date when the transaction is completed instead of when it is negotiated in hedonic analysis.

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1. Timmins (2007) argues for using an iterative procedure to solve for a new equilibrium that will converge to that which is closest to the actual equilibrium observed in the data. Calabrese et al. (2006) prove uniqueness conditional upon some key pieces of data. Kuminoff and Jarrah (2010) demonstrate how to solve for multiple equilibria in a pure characteristics horizontal sorting model framework. [↑](#footnote-ref-1)
2. Tiebout described a model in which the amount and character of housing and public goods varies across the urban landscape, and each household selects its preferred bundle of public and private goods given its income and relative prices. Every household pays for its location choice through housing costs, commuting costs, and possibly labor market returns. The household’s willingness to make these payments reveals its preferences for unpriced public goods associated with locations. [↑](#footnote-ref-2)
3. Two notable exceptions include Murphy (2010) and Klaiber and Phaneuf (2010). [↑](#footnote-ref-3)
4. Ma (2013) models households who learn through Bayesian updating about contamination at brownfield sites after assessments are made by a government agency. [↑](#footnote-ref-4)
5. Walsh (2007) was the first paper to extend this model to an endogenous attribute. [↑](#footnote-ref-5)
6. Kuminoff, Smith and Timmins (2013) make the argument that this is the same argument used by Bayer and Timmins (2007) in a different form (i.e., that the unobservable is not that important). There is, however, a subtle difference. The Bayer-Timmins instrument will have little power if observables aren’t important determinants of sorting, but even if that isn’t the case, it won’t be correlated with the unobservable. The same isn’t true of the Epple-Sieg instrument by construction. [↑](#footnote-ref-6)
7. Alternatively, the individual can be modeled as choosing over a discrete list of housing types in each location with .

   

   [↑](#footnote-ref-7)
8. The description draws heavily from a recent research paper by Depro, Timmins and O’Neil (2014), which analyzes questions concerning the causes and consequences of disproportionate exposure to pollution based on race in Los Angeles, California. [↑](#footnote-ref-8)
9. In each case, we use observations where , noting that the elements in each column of  must sum to 1. Only two of the three elements in each column can therefore be considered as independent observations. This leaves us with a small sample size of just six observations in each regression. [↑](#footnote-ref-9)
10. Specifically, the 2007 3-year ACS describes the year in which each household moved into its current residence. We find the percentage of households who moved into their current house in or before 2000. Note that, in our model, not moving corresponds simply to remaining in the same census tract, while in our data, not moving corresponds to remaining in the same house. Within-tract moves are not common (i.e., 7% of all moves), meaning that this difference should not have a significant effect on our results. [↑](#footnote-ref-10)
11. Note that, by introducing the “catch-all” location *k* = N+1, we effectively make this into a closed system, where anyone entering L.A. County comes from location N+1 and anyone leaving it moves to location N + 1. Of course, the size of the mean utility we ascribe to the catch-all location will be determined by the number of people we assume to be in location N+1 to begin with. This does not present a problem as long as we do not attempt to interpret the mean utility of that location. What is important is that the values of the mean utilities associated with the *other* locations (*k* = 1, 2,…, N) are not affected by the assumed population of N+1. We find this to indeed be the case, with our results being essentially identical regardless of whether we define the population of N+1 to be 2, 4, or 6 times the net change in population in (*k* = 1, 2,…, N) between 2000 and 2007. [↑](#footnote-ref-11)
12. In general, there is no scale associated with the vector of utility indices (i.e., one could add an arbitrary constant value to all of them and not impact the behavioral shares). As such, a normalization is required. We normalize the values such that they are mean zero. [↑](#footnote-ref-12)
13. Note that we do not have data for the “catch-all” location N+1, and the value of , *k* = N+1 depends upon the assumed population of that location. We therefore drop location N+1 from the second stage of the estimation procedure. [↑](#footnote-ref-13)
14. Gibbons et al. (2013) uses administrative data to estimate the effect of neighbourhood composition on teenagers’ educational and behavioural outcomes in England. They exploit a unique research design based on changes over time in neighbourhood composition experienced by residentially immobile students, where these changes arise purely through residential migration amongst other students in our dataset. The complete coverage of the data allows investigating heterogeneity and non-linearities in the effect of neighbourhood composition at an unprecedented level. Results show that changes in neighbourhood composition have no effects on test scores but some effects on behavioural outcomes, which are heterogeneous for boys and girls. [↑](#footnote-ref-14)