Who Values Neighborhood Diversity?

Buyer Ethnicity and Neighborhood Diversity

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Abstract

Who values neighborhood diversity in US housing markets? This paper examines the relationship between buyer ethnicity, as revealed by their names, and what they pay to own houses in more ethnically diverse neighborhoods. It provides several contributions to the literature. It evaluates the most appropriate diversity measure from among a set of reasonable alternatives motivated by prior studies. Using this measure, the empirical approach employs a simultaneous hedonic price and liquidity model of the two dimensions of equilibria in search markets to identify the extent to which diversity is capitalized into both price and ease of sale. We find ethnic clientele effects for neighborhood diversity per se as well as evidence of cultural connections between ethnic sellers and buyers. Nonetheless, houses in more diverse neighborhoods sell at a discount even when the buyer-seller ethnic mix is considered. Both buyer ethnicity and the cultural connection between sellers and buyers appear to matter, as they each modify the diversity discount paid by ethnic buyers.

INTRODUCTION

Who likes diverse neighborhoods? Relationships formed by individuals within and across ethnic groups affect individual welfare and are sometimes reflected in housing transaction outcomes (Bertrand et al., 2000; Macpherson and Sirmans, 2001; Nowak and Sayago-Gomez, 2018; Bikmetova et al., 2023). Moreover, the influences of cultural background on individuals' tastes can be complex and non-linear: according to Wong (2013), for example, people prefer to live within their ethnic group, but after reaching a saturation point, they tend to choose neighbors from other ethnic groups. While that study pertains to the Singapore market in which buyers have strong cultural affiliations, the evidence that even buyers with strong ethnic ties prefer greater neighborhood diversity after a point raises questions about diverse neighborhoods in American housing markets in which there is a mix of potential buyers with strong and weak ethnic or cultural affiliations. The question in such settings is that stated at the outset: who values neighborhood diversity?

This paper examines the extent to which different types of buyers value neighborhood diversity. Krupka (2008) studies inter-neighborhood migration patterns in American housing markets and concludes that diverse neighborhoods in terms of household incomes are not in a state of equilibrium but rather in a transitional phase. This suggests that residents do not explicitly prefer neighborhood income diversity per se since diversity is an artifact of neighborhoods in transition. A relevant question is whether this pertains to ethnic and racial diversity as well.

This study offers new empirical evidence of clientele price effects for diverse neighborhoods. It provides several contributions. Methodologically, it is the first to formally consider the most appropriate measure of diversity from a set of reasonable alternatives. Additionally, the empirical approach controls for property, neighborhood, seller, buyer, and agent characteristics using a simultaneous systems hedonic price and liquidity model that explicitly takes into account the simultaneous nature of price and selling time in the housing market. This new approach to the diversity question identifies the extent to which diversity is capitalized into price versus difficulty of sale in the search market environment.

We begin by weighing alternative neighborhood diversity measures: the U.S. Census Bureau diversity index, an inverse Herfindahl index of neighborhood ethnic/racial composition, and two measures of changing diversity that take into account the notion that diverse neighborhoods may simply be neighborhoods in transition. The Atkinson (1970) J-test for non-nested hypotheses offers support for the Census Bureau diversity index of neighborhood ethnic/racial composition from the set of four alternative measures.

Drawing from this result, we use this measure of diversity to examine buyer clientele effects in the market for existing housing. We apply an established algorithm to infer the ethnicity of buyers, sellers, and agents based on the probability their last name belongs to a particular ethnic group (Sood and Laohaprapanon 2018), adding buyer ethnicity variables and their interaction with the diversity variable to the models. Overall, houses in diverse neighborhoods sell at a discount. Although ethnic buyers also generally also pay less for diverse neighborhoods when compared with more homogeneous neighborhoods, they are willing to pay a higher price than non-ethnic buyers for houses in diverse communities. But not all ethnic groups exhibit the same preference in this regard. Probing more deeply into specific ethnicities reveals Black and Hispanic buyers pay more while Asian-Pacific-Island (API) buyers pay even less than non-ethnic buyers for houses in more diverse neighborhoods.

But, is it neighborhood diversity per se or a cultural connection with the seller that the buyer values? Empirically, the question becomes whether the diversity discount differs when buyers and sellers share ethnicity. There appears to be some benefit to sellers selling their houses to buyers from the same ethnic group; while a diverse neighborhood price discount still holds, it is smaller when the buyer and the seller share ethnicity.

The extensive real estate brokerage literature clearly shows that listing and selling agents influence buyers and sellers and, through them, transaction outcomes. Regarding cultural influences, Bikmetova et al. (2023) show that shared agent-client ethnicity may affect realized price and liquidity. Nonetheless, introducing agent ethnicity into the model shows that the agent-client ethnic mix matters, but it does not fundamentally alter conclusions about the ethnic clientele effects that appear to be driving the market value of diversity.

The final set of tests examines the value of diversity in different house price segments. Partitioning census tracts into three subsamples by median selling price reveals that no specific housing market segment appears to be driving the overall diversity price discount observed in the full sample. The diversity price discount is significant for all subsamples and is significantly greater in the highest-priced neighborhoods when compared with the lowest-priced market segment. The only reduction in liquidity is observed in the lowest-price neighborhoods. The results for ethnic buyers do, however, vary across subsamples. Discounts paid by Hispanic buyers in more diverse neighborhoods are slightly weaker in the mid-priced neighborhoods than those associated with non-ethnic buyers. The pattern observed for API buyers also differs from the full sample. These buyers show a greater discount for more diverse neighborhoods in the mid-price range when compared with non-ethnic buyers. Price discounts are the same for API and non-ethnic buyers in the highest price neighborhoods, but API buyers tend to be drawn to more liquid houses in more diverse neighborhoods than do non-ethnic buyers.

Pulling the results together, it appears that the value of neighborhood ethnic diversity varies across buyers in the identified ethnic groups. Diversity may offer value to specific buyers but it repels others. On average, buyers of all types in this market pay premia to live in less diverse neighborhoods. Nevertheless, significant clientele effects do exist. Hispanic and Black buyers pay less of a discount for diverse neighborhoods and in that sense appear to value neighborhood diversity more than non-ethnic buyers. In contrast, API buyers, on average, value diversity less. These differences may relate to decisions to integrate into a broader community or to live in a setting offering fewer constraints related to household language or culture outside the home. We expect individuals who largely abandon their ethnic culture to exhibit minimal differences in tastes and behaviors, while those retaining ethnic preferences may derive additional benefit from locating in their ethnic neighborhood. In the latter case, diversity is not attractive while ethnic similarity is.

BACKGROUND LITERATURE

We define neighborhood diversity in terms of the relative mix of residents; greater diversity implies a wider mix of a greater variety of types of residents. That said, we acknowledge that policy makers, in particular, currently tend use the term to indicate simply a greater presence of minority racial or ethnic groups. There is a substantial literature dealing with racial and ethnic effects that tends to focus on segregation in housing markets rather than neighborhoods exhibiting diverse mixes of ethnic or racial residents. For example, the seminal study by Kain and Quigley (1975) examines racial discrimination and spatial segregation in the housing markets. Macpherson and Sirmans (2001) document the effect of changing ethnic mix on market prices using a repeat-sales methodology, while Saiz and Wachter (2011) examine the impact of immigration on the neighborhood housing values using a first-difference model of average housing values. Macpherson and Sirmans (2001) find that change in racial and ethnic neighborhood composition affects housing prices and suggest that amenities attractive to specific ethnic groups may be important.

Residential mobility is influenced neighborhood changes or expectations about future changes. Individuals choose a neighborhood with known neighborhood characteristics, yet, neighborhoods can change very fast in terms of socioeconomic composition, family type composition and ethnic/racial composition. There is evidence of neighborhood ethnic composition 'tipping points' triggering mobility (Easton & Pryce, 2019; Feijten & Van Ham, 2009; Gould, 2000)[1]. Exogenous events may influence preferences for ethnic neighbors as well; Nowak and Sayago-Gomez (2018) conclude that local prejudice against Arab neighbors after the 9/11 terrorist attack translates into discounts for properties with Arab neighbors. In any case, individual ethnic tastes are complex. Wong (2013), for example, uses ethnic housing quotas in Singapore as a natural experiment and finds that Singaporeans appear to prefer living with their own ethnic group, but after reaching a neighborhood saturation point, tend to choose to live with neighbors from other ethnic groups.

In addition to buyer preferences, neighborhood composition may also reflect external constraints. In the study of ethnic determinants of housing turnover in New York City, Rosenbaum (1992) suggests that the allocation of racial/ethnic groups into separate neighborhoods is due to structural constraints in the housing market. An unknown portion of the persistent residential clustering by ethnicity or race (Rosenbaum, 1992; Borjas, 1998) is likely due to customers' or agents' prejudice (Galster and Godfrey, 2005; Zhao et al., 2006).

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[1] Political partisanship may matter, too. MacCartney et al. (2024) show that an aversion to living near members of the opposite party impacts willingness to sell homes and move.

A number of studies find evidence of rental discrimination in the U.S. King and Mieszkowski (1973) document racial discrimination in requesting differential rent payments for comparable properties. More recently, Carpusor and Loges (2006) find name-based stereotypes and racial or ethnic discrimination effects in rentals. Beyond price, bias is reflected through multiple channels, such as response rate, providing information about unit availability or the number of units available, further correspondence, or even the choice of language and politeness (Yinger, 1986; Ondrich et al., 1998; Ondrich et al., 2000; Ondrich et al., 2003; Hanson & Hawley, 2011; Hanson et al., 2011; Ewens et al., 2014). Interestingly, several studies using European data discover more ethnic discrimination in neighborhoods with a lower share of ethnic minorities (Martiniello & Verhaeghe, 2022; Carlsson & Eriksson, 2015).

More generally, there is evidence that the cultural backgrounds of buyers, sellers, and agents affect how they interact in housing transactions. A study using survey data reports that buyers felt their ethnic or cultural background was a hindrance in purchasing a house and 10% of minorities believed the seller was less favorable to them (Bond et al., 2003). Bikmetova et al. (2023) show that buyers, sellers, and their real estate agents interact differently when from the same ethnic group, although differences in transaction outcomes appear to largely reflect clients' cultural backgrounds as the mix of listing and selling agents' ethnic backgrounds does not affect selling price or liquidity. There also is some evidence that cultural backgrounds influence buyer attraction to certain neighborhood characteristics like walkability and proximity to open spaces (Dey et al., 2023; Turner & Seo, 2021). Relatedly, experimental studies find that families express heterogeneous racialized school preferences. For example, Hailey (2022) presents evidence that in New York City white and Asian families prefer white schools over black and Latino schools, Latino families prefer Latino schools over black schools, and black families prefer black schools over white schools.[2] The question is whether cultural backgrounds similarly influence buyer willingness to pay for neighborhood diversity. It is to this question we now turn.

DATA

The data set comprises sales of single family detached and townhouses over 2004-2020 in Gwinnett County, a diverse county of over 950,000 in the Atlanta metropolitan area. Sales during the covid-19 pandemic are omitted from the sample in order to avoid idiosyncratic market conditions during that period. The sample area includes ethnic enclaves and a variety of mixed neighborhoods, providing an appropriate setting for the questions addressed here. Property listing and transaction information, property characteristics, and some agent information is drawn from Multiple Listing Service (MLS) records. Selling price (*SP*) is drawn directly from MLS transaction reports. Liquidity or time on the market (*TOM*) is measured as the difference between the reported off-market date and the listing date plus one. The sample includes only houses that are at least two years old to avoid sequential sales effects and other pricing effects peculiar to new construction (Munneke et al., 2019). The sample focuses on arms-length transactions, excluding agent-related and agent owned houses, distress sales and outlier observations in the upper or lower 1% of the distributions of observed sale price or time on the market.

For agents identified in the MLS transactions data, the Georgia Real Estate Commission and the public information summarized on the BeenVerified.com website provides full names, ages and addresses, the first of which is used to identify ethnicity, as explained below. The resultant data set comprises information about agents' characteristics, including completed

[2] Historically, nearly all children in the US attend their neighborhood school. Residence-based school assignment systems suggests that a school's demographic makeup often closely resembles that of the neighborhood it serves.

transactions, age, ethnicity, and residence, information used to construct the measures of agent characteristics and transactions strategies like geographic specialization and market power.

In order to keep the process of identifying agent ethnicity manageable, the sample only includes sales in which either the listing or selling agent are full-time agents. Full-time agents are defined as participating in 3.5 or more transactions per year on average. This provides a reasonable distinction between full and part-time agents. Agents who earn the entire agent commission for both listing and bringing the buyer to 3.5 sales earn approximately 58% of the median income in Gwinnett County; most agents do not earn both listing and selling commission shares in all of the transactions in which they participate, so part-time agents earn considerably less. Nonetheless, agents on the other side of a transaction involving a full-time agent who do not meet this criterion are labeled part-time agents in the data set. The sample excludes transactions by discount brokers and companies buying and selling real estate through technology (e.g., *iBuyer*) since the literature has not yet determined how these business models affect transaction outcomes (Buchak et al., 2020).

Georgia property tax records provide the names of property buyers and sellers. The first and last name of the first individual reported as involved in the transaction is used to determine ethnicity, as explained below, or if the buyer or seller is a financial institution or investment company.

The census block group level data on neighborhood ethnic composition and diversity, explained below, are drawn from the 2010 and 2020 Census. In addition, all models include the socio-economic census tract controls related to residents' ages, education, and median household income drawn from 2010-2020 American Community Surveys. All monetary values are in 2010 dollars using the consumer price index from the Bureau of Labor Statistics. Models also include

ZIP code fixed effects to control unobserved neighborhood conditions. Year and month fixed effects in all models account for time trend and seasonality.

Merging the MLS and property tax records yields 74,591 sales during 2004 to 2019 in the full sample.

In order to measure the extent to which cultural background drives possible clientele effects on the value of neighborhood diversity, we need to identify buyer ethnicity. Sood and Laohaprapanons (2018) exploit the 2010 U.S. Census last name data and Wikipedia last name and first name data to construct probabilities of racial or ethnic identification based on the letter construction of names. This paper follows recent research applying the Sood and Laohaprapanon (2018) method to identify individuals' ethnic background from their names (Bikmetova et al., 2023; Dey et al., 2023). We use the 2010 Census-based Long Short Term Memory Networks algorithm to identify buyer, seller and agent ethnicity. US Census data classifies names into four racial groups: White, Black, Asian-Pacific Islander (API), and Hispanic. The ethnic and racial categories match those used for measuring neighborhood composition in the decadal census enumeration, increasing the consistency of neighborhood and individual ethnicity classification and their interactions. Unfortunately, the name identification algorithm identifies American Blacks with European names as White since the algorithm relies on sub-Sahara African names. One must keep this systematic error in mind when interpreting the empirical results; the errors likely bias estimates pertaining to Black buyers, sellers, or agents toward zero. White is the excluded category when examining ethnicity effects.

There are two caveats to keep in mind when using names to infer ethnicity in America (Bikmetova et al. 2023). First, the last name approach can classify individuals as ethnic who do not self-identify as such, for example, a second or later generation descendent of immigrants who has become fully integrated into broader American culture. Second, the ethnic identification algorithm yields inherently noisy results. For example, Sood and Laohaprapanon (2018) find the precision of the algorithm when applied to Wikipedia data is 73% for full names. Both types of potential misclassifications likely bias our estimates of ethnicity effects on property transactions towards zero.

Table 1 presents the list of key variables used in the various empirical models; table 2 provides summary statistics for these variables. The available appendix provides full information for the entire set of variables used in the analysis. In addition to neighborhood diversity and individual ethnicity variables in table 1, the full set of variables can be organized in the following categories: transaction outcome in terms of selling price and time on the market; property characteristics including living area, age, bedrooms, bathrooms, features, architecture, and subdivision amenities; socio-economic neighborhood characteristics and neighborhood market conditions; investor buyer or seller; and real estate agent characteristics and strategies including controls for age, experience, listing property as a coagent, dual agent representing both seller and buyer, living near client, geographic concentration of listing inventory in neighborhood, and market share of listings in neighborhood.

Table 2 reports the proportions of buyers in each ethnic category: 1.7% Black, 12.6% Hispanic, and 13.6% API. The relatively few buyers identified as Black reflects the issue pointed out earlier, that the algorithm identifies all individuals with European names as White. About 0.7% of listing agents are identified as Black, 3.4% Hispanic, and 5.1% API. The identified ethnic composition of selling agents—agents bringing buyers to transactions—are similar, with 0.5% Black, 7.5% Hispanic and 7.3% API.

EMPIRICAL ANALYSIS

The market for existing housing is a search market in which the interplay of potential sellers and buyers simultaneously determine both selling price and time on the market or liquidity.[3] In search markets price and liquidity are determined simultaneously and are therefore functions of the same exogenous variables. Turnbull and Zahirovic-Herbert (2012) use a generalized search model to derive empirical reduced form equations describing these two dimensions of equilibrium. Following that approach, the empirical framework describing the equilibrium outcome for the transaction of property *i* sold at time *t* is

$$lnSP_{it} = \boldsymbol{\alpha}\mathbf{X}_i + \beta Diversity_{it} + \boldsymbol{\sigma}\mathbf{E}_{it} + \delta_t T_{it} + u_{it} \tag{1}$$

$$lnTOM_{it} = \boldsymbol{a}\mathbf{X}_i + bDiversity_{it} + \boldsymbol{s}\mathbf{E}_{it} + d_t T_{it} + v_{it} \tag{2}$$

where $\mathbf{X}_i$ is the vector of property characteristics, neighborhood characteristics including Zip code fixed effects, investor or owner-occupier buyer and seller, and the distance-weighted number of contemporaneously listed competing houses within one mile to control for neighborhood housing market conditions.[4] $Diversity_{it}$ is the variable measuring neighborhood diversity, as described below, $\mathbf{E}_{it}$ is the vector of variables capturing ethnicities of individuals involved in the transaction, T_{it} are time period (quarterly) fixed effects and *u* and *v* are stochastic errors.[5] Some models include interaction terms, as indicated in the reported results. This is a system of reduced form equations

[3] The methodology survey by Lippman and McCall (1976) is a seminal influence on search models of housing markets. See Arnott (1989), Haurin (1988), Krainer (2001), Turnbull and Dombrow (2006), Turnbull and Zahirovic-Herbert (2012), Williams (1995), and Wheaton (1990) for a variety of theoretical approaches depicting the housing market as a search market.

[4] Following Turnbull and Zahirovic-Herbert (2012) and others, listing density measures competition from nearby houses on the market at the same time as the subject property. The variable is calculated as the distance-weighted number of houses within one mile and 20% of living area of the subject property that are listed for sale in the MLS each day the subject property is on the market.

[5] Models include variables indicating ethnic concentrations of at least 30%. None of the conclusions change when omitting these controls. Only the Hispanic neighborhood indicator is highly correlated (r = 0.6) with the diversity measure. To verify the results pick up diversity and not ethnic concentration per se, we also construct an index orthogonal to the Hispanic neighborhood indicator using the residuals from regressing the diversity index on the Hispanic neighborhood variable. Conclusions do not change when using the orthogonal variable for the diversity index in the models.

describing the solution to a set of equilibrium conditions, so cross equation correlation of errors is likely. In such settings it is appropriate to estimate this reduced form system using seemingly unrelated regression (SUR) in order to obtain asymptotically efficient error estimates.

The first question concerns how to measure diversity. The first measure is the diversity index, *DI*, constructed by the U.S. Census Bureau. This index measures the probability that a random draw from the census tract population will be individuals from different ethnic groups; we use the nearest census decade measure for each year in our sample. The second diversity measure is the Herfindahl index of neighborhood ethnic/racial composition, *HI*, inverted so that a higher value indicates greater diversity. In addition, motivated by Macpherson and Sirmans (2001) and Krupka (2008), we also allow for the possibility that diverse neighborhoods may be neighborhoods in transition with the implication that the direction of transition matters. We therefore also consider two measures that capture changes in diversity, ΔDI and ΔHI, in addition to the census diversity index and inverse Herfindahl level variables, where changes are calculated over the census decade.

Table 3 reports the estimates for each diversity measure in the SUR system (1)-(2); complete model estimates are available in the available appendix. The *DI* and *HI* coefficients indicate that houses in more diverse neighborhoods sell at a significant price discount but exhibit negligible differences in liquidity when compared with otherwise identical houses in less diverse neighborhoods. When measured at means, the estimates imply that greater diversity is associated with price discounts of \$29,795 and \$24,493, respectively. The estimates for changes in diversity differ considerably. The ΔDI price equation coefficient is significantly positive, indicating houses in neighborhoods with increasing diversity sell at a premium of \$3,311 when evaluated at means, with no significant liquidity effects. In contrast, increases in the inverse Herfindahl index, ΔHI, have no price effect but a marginally significant (10% level) and modest increase in liquidity of 0.37 days on the market at the mean.

The implications for diversity on transaction outcomes vary widely across the measures reported in table 3. Both level measures provide strong evidence that typical buyers do not value more diverse neighborhoods. The change measures provide divergent pictures, with one indicating buyers pay more for houses in neighborhoods with increasing diversity over time and the other portraying the increasing diversity effect as a minor improvement in liquidity signifying that is it easier to sell houses in more diverse neighborhoods. The difference in results emphasizes how important it is to identify which of these four alternative diversity measures is appropriate. Each diversity measure is non-nested in the sense that it cannot be derived as a special case of any of the others. Therefore, we apply the Atkinson (1970) non-nested hypotheses J-test to assess the alternatives. To do so, we use seemingly unrelated regression (SUR) to estimate the reduced form equation system for selling price and time on the market and apply the J-test to each equation.

Table 4 reports the correlations between the alternative diversity measures and the results of the J-test for each pair of models. The top correlation matrix shows that *DI* and *HI* are highly correlated (r = 0.71). *DI* and ΔDI are highly negatively correlated (r = -0.61) while the *HI* and difference measures are more modestly correlated. The negative *DI* and ΔDI correlation suggests that highly diverse neighborhoods tend to become less diverse over time, and neighborhoods with ethnic concentrations tend to become more diverse over time, a mean-reversion picture not fully consistent with the income mix conclusions of Krupka (2008).

For the J-tests reported in the second and third matrices, models taking the role of the maintained hypothesis are given in each row; models taking the role of the alternative hypothesis are listed in the columns. The second matrix reports the results for the price equation and the bottom matrix reports the results for the liquidity equation. Looking at the price equation first, notice that no single model dominates the others. All are rejected in favor of multiple alternative hypotheses. Turning to the liquidity equation tests reported in the bottom matrix, however, we see that the *DI* model is only rejected by the *HI* model, but all of the other models are rejected by the *DI* model while the *HI* model does not dominate either of the change models. The liquidity equation results therefore support for the *DI* model over the other 3. Drawing the information together, the J-statistics for pair-wise tests of the four models do not provide unambiguous support for any single model over all others, but the liquidity results nonetheless show the strongest support for the census diversity index of neighborhood ethnic/racial composition among the alternatives. Therefore, the models used here all use the Census Bureau diversity index *DI.*

Table 5 adds ethnic buyer and seller variables *B_Ethnic*, *S_Ethnic*, and interactions with *DI*. *B_Ethnic* is a dummy variable identifying Black, Hispanic, or API buyers; *S_Ethnic* is similarly defined for sellers. The *DI* diversity coefficient is robust across the models in Tables 3 and 5; adding the additional controls in table 5 do not affect that result. When including the additional ethnicity variables, the *DI* coefficient in table 5 picks up the discount non-ethnic buyers pay for houses in more diverse neighborhoods. The coefficient on the interaction term *DI*B_Ethnic* in model (1) in the price equation shows that ethnic buyers pay the same discount as non-ethnic buyers for properties in more diverse areas. The significant negative coefficient in the liquidity equation, however, indicates that ethnic buyers tend to purchase houses with shorter exposure to the market in more diverse neighborhoods. Model (2) adds ethnic seller variables. Clearly, the ethnic buyer and non-ethnic diversity results are unaffected by the addition of these variables.

Bikmetova et al. (2023) provide evidence that the mix of buyer and seller ethnicities affects transaction outcomes. The variable *Same_B_S* indicates that both parties in the transaction share the same ethnic category. The negative price equation and positive *TOM* equation coefficients show significantly lower selling price and longer time on the market in such transactions. The significant but modest coefficient on the interaction term *DI*Same_B_S* in the price equation reveals slightly higher selling price but no difference in liquidity for transactions between ethnic parties in more diverse neighborhoods when compared with less diverse neighborhoods. The interaction variable controls for sales to ethnic buyers, so the *DI*S_Ethnic* results in the table shows that ethnic sellers in diverse neighborhoods obtain higher prices when selling to non-ethnic buyers. This yields a diverse neighborhood discount for these sellers that is approximately one half that of non-ethnic sellers.

To better identify clientele effects, table 6 breaks out separate ethnic categories for buyers, *B_Black*, *B_Hispanic*, *B_API*, and similarly for sellers. Model (1) in the table includes buyer ethnic variables, (2) adds seller ethnic variables, and (3) adds agent ethnic variables. The non-ethnic *DI* coefficients in both price and liquidity equations are robust across specifications. The individual ethnic categories in all models show Black and Hispanic buyers pay significantly less and API buyers pay significantly more than non-ethnic buyers in general. Looking at diverse neighborhoods, though, the *DI* interaction terms with buyer ethnicity variables show Black and Hispanic buyers pay a discount for diversity of about one half that obtained by non-ethnic buyers with no differences in liquidity effects. On the other hand, API buyers pay significantly less than non-ethnic buyers for houses in more diverse neighborhoods, and buy more liquid houses.

Table 6 model (2) includes seller ethnic controls. Black, Hispanic, and API sellers all sell at lower prices than non-ethnic sellers in general and API sellers take longer to sell their houses.

The *DI* interaction terms with seller ethnicity yield similar results for all, indicating more modest diversity discounts than those for non-ethnic sellers. There is weak evidence (10% level) that API sellers sell such properties faster than other ethnic sellers or non-ethnic sellers. Finally, the *Same_B_S* and interaction variables yield results seen earlier: transactions involving buyers and sellers from the same ethnic group occur at lower prices and longer time on the market and have modestly lower diversity price discounts.[6]

The ethnic mix of buyers and sellers affect transaction outcomes even though buyers and sellers do not communicate directly with each other; they communicate through the listing and selling agents involved in the transaction, indicated by *LA* and *SA*, respectively. Model (3) in the table includes agent ethnicity variables in order to examine the extent to which agent ethnicity affects outcomes. Adding these variables does not significantly alter the other key buyer and seller and diversity estimates, which indicates that agent characteristics are not driving or biasing previously discussed results when left out of the equations. Looking at the agent ethnicity estimates, *LA_Hispanic* and *LA_API* coefficients indicate that these agents sell properties they represent for lower prices. There is weak evidence (10% level) that API agents take a longer time to sell these houses. In contrast, selling agents (those bringing buyers to the transaction) in every one of the identified ethnic categories obtain lower prices for buyers. Buyers working with API agents tend to purchase more liquid houses while buyers working with Hispanic agents tend to purchase less liquid houses. Shared agent-client ethnicity does not matter for listing agents (*Same_LA_S*) but does lead to buyers pursuing less liquid properties for selling agents (*Same_SA_B*). The effect of shared agent-client ethnicity on the diversity discount also differ for listing and selling agents. For listing agents, there is only marginally significant evidence that

[6] While Wong (2013) finds tipping points in Singapore where diversity discounts diminish, tests for nonlinear diversity and interaction effects provide no evidence of a similar phenomenon in our data.

shared ethnicity with their clients reduce the diversity discount. For selling agents, shared ethnicity with buyers leads to purchases of more liquid houses in more diverse neighborhoods.

All of the models discussed above include extensive controls for property and neighborhood characteristics in order to reduce heterogeneity. In an effort to further reduce possible unobserved heterogeneity, Tables 7 and 8 partition the sample into census tracts with median selling prices in the lowest, middle, and top third of the full sample. Table 7 reports key estimates for the model with buyer ethnicity variables and Table 8 for the complete model. The *DI* coefficients show greater price discounts for higher priced neighborhoods than lower priced neighborhoods. Only the lowest price segment sample exhibits significantly longer selling time for houses in more diverse neighborhoods. Overall, the pattern of results reduce concern that diverse neighborhoods generate lower prices because of unobserved undesirable characteristics not captured in the data.

There is evidence of cultural clientele effects on the market pricing of diversity, although the pattern differs from that observed in the full sample and differs across price segments in this market. In the lowest price segment, API buyers again pay less than other ethnic and non-ethnic buyers for houses in more diverse neighborhoods. In the medium price range, there is weak evidence of shorter time on the market as well. In the high price range, however, there is no significant price effect but API buyers pursue more liquid houses as in the medium price range. Hispanic buyers pay less of a discount for more diverse neighborhoods than other ethnic and non-ethnic buyers. The models in table 8 include seller and agent ethnic effects; as in the full sample analysis, the buyer clientele conclusions are largely unaffected by the inclusion of the additional controls in the model.

CONCLUSION

This paper considers the question: who likes ethnically diverse neighborhoods? In particular, does a buyer's cultural background matter in this regard? Empirical evidence from an Atlanta, GA, market for existing housing offers strong evidence that buyers are willing to purchase houses in more diverse neighborhoods only if they can do so at a discount. Nonetheless, there are significant patterns; buyers with Black or Hispanic names discount houses in more diverse neighborhoods somewhat less than Whites while buyers with Asian-Pacific-Island names discount diverse neighborhoods more.

In order to reduce unobserved heterogeneity, we also examine market segments comprising neighborhoods falling into the lowest third median selling price, the middle third, and the upper third. How neighborhood diversity affects house prices varies significantly across neighborhoods in different price segments. The overall percentage discount for houses in more diverse areas is greater for higher price neighborhoods than lower price neighborhoods, a pattern suggesting that the diversity discount does not reflect unobserved negative characteristics in lower priced neighborhoods. The ethnic effects imply a lower discount paid by Hispanics in the mid-price range segment and a greater price discount for Asian-Pacific-Island buyers in the lowest price segment.

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Table 1 - Key Variables definition

Variable	Description and Data Source
Diversity Measures	
DI	Diversity index. Probability that a random draw from census tract population will be individuals from different ethnic groups in the nearest census for each year in our sample. Source: US Census Bureau
HI	Herfindahl index of neighborhood ethnic/racial composition. Inverse of the sum of the three largest squared shares of ethnic groups so that higher value indicates greater diversity. Source: US Census Bureau
∆DI	Change in diversity index over the census decade. Source: US Census Bureau
∆HI	Change in Herfindahl index over the census decade. Source: US Census Bureau
Ethnicity	
S_Ethnic/B_Ethnic	Indicator variable for seller/buyer identified as Black, Hispanic, or API. Source: Authors' analysis of names from Gwinnett Property Records
LA_Ethnic / SA_Ethnic	Indicator variable for listing/selling agent identified as Black, Hispanic, or API. Source: Authors' analysis of names from MLS, GREC
*DI*S_Ethnic/DI*B_Ethnic*	An interaction term for *DI* and *S_Ethnic*/*B_Ethnic*
Same_S_B	Indicator variable for both buyer and seller identified with same ethnicity.
*DI*Same_S_B*	Interaction term for *DI* and *Same_S_B*
Same_LA_S	Indicator variable for both listing agent and seller identified with same ethnicity.
Same_SA_B	Indicator variable for both selling agent and buyer identified with same ethnicity.
*DI*Same_LA_S*	Interaction term for *DI* and *Same_LA_S*
*DI*Same_SA_B*	Interaction term for *DI* and *DI_Same_SA_B*

Table 2

Summary - Key variables

This table reports summary statistics for the key variables associated with completed transactions over the sample of Gwinnett County MLS sales data over 2004-2020. Columns 1, 2, and 3 present min, mean, and max values for all sold properties, respectively.

	Listed			Sold		
	Number of Observations:114758			Number of Observations: 74591		
	Min	Mean	Max	Min	Mean	Max
	(1)	(2)	(3)	(4)	(5)	(6)
Listing Price	44495.49	217316.55	859855.85	44495.49	204147.09	739852.19
Selling Price				40714.82	199463.51	621935.52
TOM	2	82.48	413	2	54.94	413
NE_BLACK	0	0.1884	1	0	0.1876	1
NE_ASIAN	0	0.0241	1	0	0.0237	1
NE_HISP	0	0.0963	1	0	0.0926	1
DI	19.9	64.4772	93	19.9	64.6154	93
HI	9.9466	56.067	81.7672	9.9466	57.4408	81.7672
ΔDI	-65.6	1.5795	34.5	-65.6	1.7675	34.5
ΔHI	-20.8559	14.9493	44.3231	-20.8559	15.0817	44.3231
B_Ethnic				0	0.2915	1
*DI*B_Ethnic*				0	19.9898	93
B_Black				0	0.0175	1
B_Hispanic				0	0.1316	1
B_API				0	0.1425	1
*DI*B_Black*				0	1.1188	91.9
*DI*B_Hispanic*				0	9.0966	93
*DI*B_API*				0	9.7745	93
S_Ethnic				0	0.1329	1
*DI*S_Ethnic*				0	9.0132	93
S_Black				0	0.0131	1
S_Hispanic				0	0.0531	1
S_API				0	0.0666	1
*DI*S_Black*				0	0.8416	92.9
*DI*S_Hispanic*				0	3.5988	93
*DI*S_API*				0	4.5728	93
SAME_S_B				0	0.0199	1
*DI*SAME_S_B*				0	2.3371	93
LA_Black	0	0.0068	1	0	0.0069	1
LA_Hispanic	0	0.0455	1	0	0.0338	1
LA_API	0	0.0586	1	0	0.0505	1
SA_Black				0	0.0046	1
SA_Hispanic				0	0.0745	1
SA_API				0	0.0725	1
SAME_LA_S				0	0.0339	1
SAME_SA_B				0	0.0927	1
*DI*SAME_LA_S*				0	2.3985	93
*DI*SAME_SA_B*				0	6.4733	92.9

Table 3

Price-Liquidity SUR Model - Different Diversity Measures

This table reports coefficient estimates from SUR regressions with the natural logarithm of selling price lnSP and natural logarithm of days on market lnTOM . All models include property, neighborhood and census tract level variables, agent-level variables ZIP code and year-quarter fixed effects. The full estimates are presented in the available Appendix. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)		(2)		(3)		(4)	
	lnSP	lnTOM	lnSP	lnTOM	lnSP	lnTOM	lnSP	lnTOM
DI	-0.0026***	0.0003						
	(-36.9025)	(1.3536)						
HI			-0.0018***	-0.0002				
			(-24.1174)	(-0.9838)				
ΔDI					0.0011***	-0.0004		
					(12.8351)	(-1.3875)		
ΔHI							0.0001	-0.0005*
							(0.7467)	(-1.7179)
Selling quarter FE	yes	yes	yes	yes	yes	yes	yes	yes
ZIP code FE	yes	yes	yes	yes	yes	yes	yes	yes
Housing, neighborhood and agent (non-ethnic) characteristics	yes	yes	yes	yes	yes	yes	yes	yes
Adj R-sq	0.8177	0.1127	0.8158	0.1126	0.8148	0.1127	0.8144	0.1127
N. obs	74591		74591		74591		74591	

Table 4

Panel A - Correlation matrix for Alternative Diversity Measures

Panel A table presents the Pearson correlation coefficients and p values for four alternative diversity variables for the sample of completed transactions over the sample of Gwinnett County MLS sales data over 2004-2020. Panels B and C present the J-tests for lnSP and lnTOM equations for four alternative diversity variables for the sample of completed transactions over the sample of Gwinnett County MLS sales data over 2004-2020. For each null hypothesis at the left, the number in the row is the J-test statistic (with the p-value in the second row) for the alternate hypothesis at the head of the column. The J-statistic for each diversity measure is estimated with SUR.

Pearson Correlation Coefficients, N = 74,591
Prob > |r| under H0: Rho=0

	DI	*HI*	*ΔDI*	*ΔHI*
DI	1.000	0.707	-0.608	-0.317
		<.0001	<.0001	<.0001
HI	0.707	1.000	-0.246	-0.323
	<.0001		<.0001	<.0001
ΔDI	-0.608	-0.246	1.000	0.721
	<.0001	<.0001		<.0001
ΔHI	-0.317	-0.323	0.721	1.000
	<.0001	<.0001	<.0001	

Panel B - J-Test for lnSP Alternative Diversity Measures

	Alternative Hypothesis			
Maintained Hypothesis	*DI*	*HI*	*ΔDI*	*ΔHI*
DI		-1.06	0.12	-10.58
		<0.001	0.131	<0.001
HI	1.59		0.60	-9.57
	<0.001		<0.001	<0.001
ΔDI	0.99	0.93		-54.29
	<0.001	<0.001		<0.001
ΔHI	1.05	1.09	3.73	
	<0.001	<0.001	<0.001	

Panel C - J-Test for lnTOM Alternative Diversity Measures

Maintained	Alternative Hypothesis			
Hypothesis	*DI*	*HI*	*ΔDI*	*ΔHI*
DI		7.81	0.77	0.87
		<0.001	0.31	0.15
HI	5.82		1.23	1.29
	<0.001		0.10	0.03
ΔDI	0.75	1.41		1.19
	0.33	0.18		0.30
ΔHI	0.75	1.68	-0.27	
	0.32	0.12	0.85	

Table 5

Price-Liquidity SUR Model – Ethnic Clientele Effect

This table reports coefficient estimates of key variables from SUR regressions with the natural logarithm of selling price lnSP and natural logarithm of days on market lnTOM. All models include property, neighborhood and census tract level variables, agent-level variables, ZIP code and year-quarter fixed effects. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)		(2)	
	lnSP	lnTOM	lnSP	lnTOM
DI	-0.0026***	0.0004*	-0.0028***	0.0004
	(-32.8126)	(1.7287)	(-32.8885)	(1.4825)
B_Ethnic	-0.0311***	0.0547**	-0.0391***	0.0378
	(-3.6752)	(2.0535)	(-4.5011)	(1.3862)
*DI*B_Ethnic*	0.0001	-0.0007*	0.0001	-0.0006
	(0.4199)	(-1.7497)	(0.7901)	(-1.4103)
S_Ethnic			-0.1012***	0.0627*
			(-8.4076)	(1.6616)
*DI*S_Ethnic*			0.0011***	-0.0002
			(6.1668)	(-0.3964)
Same_S_B			-0.0134**	0.0457**
			(-2.3249)	(2.525)
*DI*Same_S_B*			0.0003***	-0.0001
			(4.3723)	(-0.4821)
Selling quarter FE	yes	yes	yes	Yes
ZIP code FE	yes	yes	yes	Yes
Housing, neighborhood and agent (non-ethnic) characteristics	yes	yes	yes	Yes
Adj R-sq	0.8225	0.1127	0.8239	0.117
Observations	74591		74591	

Table 6

Price-Liquidity SUR Model - Ethnic Categories

This table reports coefficient estimates for key variables from SUR regressions with the natural logarithm of selling price lnSP and natural logarithm of days on market lnTOM . All models include property, neighborhood and census tract level variables, agent-level variables, ZIP code and year-quarter fixed effects. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)		(2)		(3)	
	lnSP	lnTOM	lnSP	lnTOM	lnSP	lnTOM
DI	-0.0026***	0.0005*	-0.0028***	0.0004*	-0.0028***	0.0005*
	(-32.8721)	(1.9302)	(-32.9357)	(1.6691)	(-32.8014)	(1.88)
B_Black	-0.0778***	0.0208	-0.092***	0.0009	-0.0913***	-0.0016
	(-2.7821)	(0.2363)	(-3.2832)	(0.0097)	(-3.2576)	(-0.0183)
B_ Hispanic	-0.0831***	0.0211	-0.0934***	0.002	-0.0913***	-0.0408
	(-7.1767)	(0.5785)	(-7.9214)	(0.0549)	(-7.1355)	(-1.0165)
B_API	0.027**	0.1013***	0.0216*	0.0809**	0.0233*	0.0462
	(2.3118)	(2.7559)	(1.821)	(2.1751)	(1.8157)	(1.1493)
*DI*B_Black*	0.001**	0	0.0011***	0.0002	0.0011***	0.0003
	(2.2164)	(0.0167)	(2.5941)	(0.1823)	(2.5788)	(0.2063)
*DI*B_ Hispanic*	0.0009***	0.0004	0.0009***	0.0005	0.0009***	0.001*
	(5.1519)	(0.7747)	(5.5157)	(1.0227)	(5.0247)	(1.7589)
*DI*B_API*	-0.0009***	-0.002***	-0.0009***	-0.0018***	-0.0009***	-0.0013**
	(-5.1502)	(-3.694)	(-5.022)	(-3.3698)	(-4.8502)	(-2.1386)
S_API			-0.0947***	0.1398***	-0.0836***	0.1288**
			(-5.6206)	(2.649)	(-4.491)	(2.209)
S_Black			-0.074**	-0.0292	-0.0731**	-0.0325
			(-2.1985)	(-0.2763)	(-2.1699)	(-0.3084)
S_ Hispanic			-0.1125***	0.0186	-0.1054***	0.0105
			(-6.1538)	(0.325)	(-5.5192)	(0.1763)
*DI*S_API*			0.001***	-0.0012	0.0009***	-0.0014
			(4.2376)	(-1.6187)	(3.1381)	(-1.5869)
*DI*S_Black*			0.0007	0.0011	0.0007	0.0012
			(1.2881)	(0.7038)	(1.2586)	(0.7148)
*DI*S_ Hispanic*			0.0012***	0.0002	0.0011***	0.0002
			(4.5379)	(0.2921)	(3.9363)	(0.2613)
SAME_S_B			-0.0146**	0.0396**	-0.0143**	0.0338*
			(-2.5247)	(2.1811)	(-2.4606)	(1.8571)
DI_SAME_S_B			0.0004***	0.0001	0.0003***	0
			(4.7812)	(0.3045)	(4.6338)	(-0.0289)

Table 6 – Continued

	(1)		(2)		(3)	
	lnSP	lnTOM	lnSP	lnTOM	lnSP	lnTOM
LA_API					-0.0088**	0.0163
					(-2.1617)	(1.2751)
LA_Black					0.0072	0.0293
					(0.8604)	(1.1175)
LA_ Hispanic					-0.01**	-0.001
					(-2.265)	(-0.0725)
SA_API					-0.0033	-0.0439***
					(-0.7872)	(-3.3338)
SA_Black					-0.0211**	-0.0295
					(-2.0053)	(-0.895)
SA_ Hispanic					-0.0115***	0.0054
					(-2.9244)	(0.4331)
SAME_LA_S					-0.0262	0.0759
					(-0.9249)	(0.8563)
SAME_SA_B					0.0031	0.1472***
					(0.1805)	(2.7741)
*DI*SAME_LA_S*					0.0006	-0.0003
					(1.3866)	(-0.2682)
*DI*SAME_SA_B*					0	-0.0017**
					(0.1472)	(-2.3521)
Selling quarter FE	yes	yes	Yes	yes	yes	yes
ZIP code FE	yes	yes	Yes	yes	yes	yes
Housing, neighborhood and agent (non-ethnic) characteristics	yes	yes	Yes	yes	yes	yes
Aqj R-sq	0.8183	0.1137	0.8188	0.1144	0.8188	0.1149
N. obs	74591		74591		74591	

Table 7

Price-Liquidity SUR Model - Subsample Analysis

This table reports coefficient estimates for key variables from SUR regressions with the natural logarithm of selling price lnSP and natural logarithm of days on market lnTOM. All models include property, neighborhood and census tract level variables, agent-level variables, ZIP code and year-quarter fixed effects. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Subsample					
	Selling price in the bottom Census Tract tercile		Selling price in the middle Census Tract tercile		Selling price in the top Census Tract tercile	
	(1)		(2)		(3)	
	lnSP	lnTOM	lnSP	lnTOM	lnSP	lnTOM
DI	-0.0014***	0.0013	-0.0021***	-0.0002	-0.0024***	0.0001
	(-5.6928)	(1.6007)	(-14.5907)	(-0.4191)	(-20.2445)	(0.2142)
B_Black	-0.0248	0.1344	-0.0702	0.0385	-0.0754*	-0.0721
	(-0.3881)	(0.6336)	(-1.4122)	(0.2405)	(-1.8677)	(-0.5433)
B_Hispanic	0.0403*	-0.0485	-0.0968***	-0.0065	-0.0566***	0.1143*
	(1.7098)	(-0.6189)	(-4.6635)	(-0.0967)	(-2.7805)	(1.7091)
B_API	0.0494	0.0058	0.0182	0.0945	-0.0534***	0.0883
	(1.6435)	(0.0576)	(0.7983)	(1.2896)	(-3.2354)	(1.6274)
*DI*B_Black*	0.0004	-0.0017	0.0007	-0.0006	0.001	0.0019
	(0.4033)	(-0.5551)	(0.9084)	(-0.2481)	(1.4588)	(0.8609)
*DI*B_Hispanic*	-0.0007**	0.0012	0.001***	0.0009	0.0003	-0.0009
	(-2.2004)	(1.2011)	(3.3272)	(0.879)	(1.0598)	(-0.853)
*DI*B_API*	-0.0011***	-0.0008	-0.0006**	-0.0018*	0.0004	-0.0017**
	(-2.8017)	(-0.6254)	(-1.9857)	(-1.6936)	(1.5074)	(-2.0319)
Selling quarter FE	yes	yes	yes	yes	yes	yes
ZIP code FE	yes	yes	yes	yes	yes	yes
Housing, neighborhood and agent (non-ethnic) characteristics	yes	yes	yes	yes	yes	yes
Adj R-sq	0.7807	0.1291	0.7591	0.1193	0.8149	0.107
Observations	14467		26150		30299	

Table 8
Price-Liquidity SUR Model - Subsample Analysis

This table reports coefficient estimates for key variables from SUR regressions with the natural logarithm of selling price lnSP and natural logarithm of days on market lnTOM. All models include property, neighborhood and census tract level variables, agent-level variables, ZIP code and year-quarter fixed effects. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Subsample					
	Selling price in the bottom Census Tract tercile		Selling price in the middle Census Tract tercile		Selling price in the top Census Tract tercile	
	(1)		(2)		(3)	
	lnSP	lnTOM	lnSP	lnTOM	lnSP	lnTOM
	-0.0016***	0.001	-0.0023***	0.0001	-0.0023***	0
DI	(-5.7584)	(1.1343)	(-14.6953)	(0.1116)	(-18.991)	(-0.0885)
	-0.0401	0.0622	-0.0819	0.0228	-0.0784*	-0.0862
B_Black	(-0.6183)	(0.293)	(-1.64)	(0.1424)	(-1.9452)	(-0.6521)
	0.014	-0.2393***	-0.1078***	-0.0149	-0.0612***	0.1022
B_Hispanic	(0.5041)	(-2.6225)	(-4.633)	(-0.2002)	(-2.8947)	(1.4755)
	0.0284	-0.1481	0.007	0.0984	-0.0581***	0.068
B_API	(0.8548)	(-1.3628)	(0.2758)	(1.2109)	(-3.1869)	(1.1379)
	-0.1076	-0.0292	-0.071	0.1008	0.0033	-0.2584
S_Black	(-1.4453)	(-0.1195)	(-1.2139)	(0.5385)	(0.0654)	(-1.5803)
	0.0082	0.066	-0.1715***	-0.009	-0.0848***	-0.0322
S_Hispanic	(0.2036)	(0.5008)	(-4.8564)	(-0.0798)	(-2.9223)	(-0.3377)
	-0.0672	0.2601*	-0.0838**	0.2741**	-0.001	0.0736
S_API	(-1.517)	(1.7916)	(-2.289)	(2.3401)	(-0.0369)	(0.863)
	0.0005	-0.0008	0.0008	-0.0005	0.001	0.002
*DI*B_Black*	(0.5296)	(-0.2538)	(1.0715)	(-0.2025)	(1.5062)	(0.9352)
	-0.0004	0.0037***	0.0012***	0.0005	0.0004	-0.001
*DI*B_Hispanic*	(-1.2034)	(3.018)	(3.4391)	(0.4624)	(1.1409)	(-0.9119)
	-0.0009**	0.0012	-0.0005	-0.0019	0.0004	-0.0016*
*DI*B_API*	(-2.1278)	(0.8186)	(-1.4925)	(-1.6411)	(1.4423)	(-1.6702)
	0.0012	0.0001	0.0005	-0.0007	-0.0005	0.0053**
*DI*S_Black*	(1.1489)	(0.0162)	(0.6014)	(-0.2355)	(-0.6645)	(1.9854)
	-0.0003	-0.0006	0.002***	0.0004	0.0009**	0.0014
*DI*S_Hispanic*	(-0.5521)	(-0.3071)	(3.9098)	(0.2551)	(1.9681)	(0.901)
	0.0007	-0.0028	0.001*	-0.0034**	-0.0005	-0.0006
*DI*S_API*	(1.2009)	(-1.4367)	(1.9218)	(-2.0264)	(-1.1591)	(-0.4362)
	0.0067	0.108*	0.0112	-0.0135	0.0024	0.0343
LA_Black	(0.3351)	(1.6562)	(0.8535)	(-0.3219)	(0.1994)	(0.8741)
	0.0111	0.0028	-0.0183***	-0.0055	-0.0191***	0.0129
LA_Hispanic	(1.3165)	(0.1001)	(-2.6458)	(-0.2485)	(-2.6774)	(0.5513)
	0.0143*	0.0144	-0.0195***	0.0198	-0.0225***	0.0063
LA_API	(1.8876)	(0.5804)	(-2.8593)	(0.9074)	(-3.4336)	(0.2927)
	-0.0134	-0.0027	-0.0193	-0.0386	-0.0296**	-0.0493
SA_Black	(-0.5958)	(-0.0362)	(-1.1134)	(-0.6955)	(-1.9651)	(-1)
	-0.014*	-0.0208	-0.0169***	0.0033	-0.0122**	0.0322
SA_Hispanic	(-1.7387)	(-0.7897)	(-2.7193)	(0.1656)	(-1.9903)	(1.6051)
	-0.0146*	-0.0506*	-0.0029	-0.0829***	-0.0006	-0.0132
SA_API	(-1.752)	(-1.8485)	(-0.4282)	(-3.7858)	(-0.0859)	(-0.6217)

Table 8 – Continued

	(1)		(2)		(3)	
	lnSP	lnTOM	lnSP	lnTOM	lnSP	lnTOM
Same_LA_S	-0.0121	0.0534	0.0628	-0.0272	-0.1027**	0.2354
	(-0.2327)	(0.3125)	(1.1802)	(-0.1597)	(-2.1615)	(1.5107)
Same_SA_B	0.0389	0.2814***	-0.0026	0.0375	0.0118	0.0487
	(1.1885)	(2.6256)	(-0.084)	(0.3839)	(0.4037)	(0.5084)
*DI*Same_LA_S*	0.0001	-0.0001	-0.0006	0.0012	0.002***	-0.0024
	(0.149)	(-0.0445)	(-0.8063)	(0.519)	(2.7456)	(-1.0269)
*DI*Same_SA_B*	-0.0003	-0.0036**	0.0001	0.0004	-0.0001	-0.0004
	(-0.7717)	(-2.5683)	(0.1677)	(0.2683)	(-0.2266)	(-0.2974)
Selling quarter FE	Yes	yes	yes	yes	yes	yes
ZIP code FE	Yes	yes	yes	yes	yes	yes
Housing, neighborhood and agent (non-ethnic) characteristics	Yes	yes	yes	yes	yes	yes
Adj R-Sq	0.7796	0.1356	0.7605	0.1246	0.8158	0.1113
Observations	12986		23972		28452	

AVAILABLE APPENDIX

Table 1.A - Variables definition

Variable	Description and Data Source
Transaction outcome	
lnSP	The natural logarithm of one plus selling price. Source: MLS
lnTOM	The natural logarithm of one plus days on the market. Source: MLS
Property characteristics	
lnSQFT	The natural logarithm of one plus total property area. Source: MLS
lnAGE	The natural logarithm of one plus property age in years. Source: MLS
lnBR	The natural logarithm of one plus number of bedrooms. Source: MLS
lnBAF	The natural logarithm of one plus number of full bathrooms. Source: MLS
lnBAH	The natural logarithm of one plus number of half bathrooms. Source: MLS
TH	The indicator variable equal 1 for attached townhouse properties and 0 otherwise. Source: MLS
Fireplace	Number of fireplaces in the property. Source: MLS
Brickframe	The indicator variable equal 1 for properties with brick frame and 0 otherwise. Source: MLS
Brick3sided	The indicator variable equal 1 for properties with 3-sided brick frame and 0 otherwise. Source: MLS
Brick4sided	The indicator variable equal 1 for properties with 4-sided brick frame and 0 otherwise. Source: MLS
Brickfront	The indicator variable equal 1 for properties with brick front and 0 otherwise. Source: MLS
Vacant	The indicator variable equal 1 for vacant properties and 0 otherwise. Source: MLS
STO_onestory	The indicator variable equal 1 for one-story properties and 0 otherwise. Source: MLS
AMEN_neighborhoodassoc	The indicator variable equal 1 for properties with a neighborhood association and 0 otherwise. Source: MLS
AMEN_park	The indicator variable equal 1 for properties near parks and 0 otherwise. Source: MLS
AMEN_playground	The indicator variable equal 1 for properties near playgrounds and 0 otherwise. Source: MLS
AMEN_walkschool	The indicator variable equal 1 for properties near schools and 0 otherwise. Source: MLS
AMEN_golfcourse	The indicator variable equal 1 for properties near a golf course and 0 otherwise. Source: MLS
AMEN_gatedcommunities	The indicator variable equal 1 for gated properties and 0 otherwise. Source: MLS
Neighborhood Characteristics	
Listing Density	Competing listings per day on market.
frac_below_18	The fraction of population below 18 years old in a census tract. Source: American Community Survey, 2010-2020
frac_65_over	The fraction of population over 16 years old in a census tract. Source: American Community Survey, 2010-2020
frac_bach_higher	The fraction of population holding bachelor's degree or higher in a census tract. Source: American Community Survey, 2010-2020
LnMedian_income	Median household income in the past 12 months in a census tract. Source: American Community Survey, 2010-2020

Table 1.A - Continued

Variable	Description and Data Source
NE_black	The indicator variable equal 1 for census block groups with proportion of Black population exceeding 33.3%. Source: Census 2010
NE_asian	The indicator variable equal 1 for census block groups with proportion of Asian population exceeding 33.3%. Source: Census 2010
NE_hisp	The indicator variable equal 1 for census block groups with proportion of Hispanic population exceeding 33.3%. Source: Census 2010
Buyer and seller characteristics	
Investor_seller	The indicator variable equal 1 for properties sold by a company (rental properties). Source: Gwinnett County Property records
Investor_buyer	The indicator variable equal 1 for properties sold by a company (rental properties). Source: Gwinnett County Property records
Agent characteristics	
LA_age25below/ SA_age25below	The indicator variable equals 1 for listing (selling) agents below 25 years old
LA_age65plus/ SA_age65plus	The indicator variable equals 1 for listing (selling) agents over 65 years old
LA_parttimer / SA_parttimer	The indicator variable equal 1 for listing (selling) agents selling less than 3.5 on average during years active, or not identified agents. Source: MLS
lnLA_Vol / lnSA_Vol	The natural log of one plus the number of completed transactionson *both* the listing and selling sides (regardless of an agent specialization) over the past 12 months. Source: MLS
lnLA_farming	The ratio of listing agent's properties in a census tract to the agent's total inventory in that year. Source: MLS
lnLA_mkt_share	The ratio of listing agent's properties to all listed properties in the census tract in that year. Source: MLS
LA_neighborhood / SA_neighborhood	The indicator variable equal 1 for listing (selling) agents residing under the same ZIP-code as property sold and 0 otherwise. Source: GREC, Public records
LA_coagent	The indicator variable equal 1 for listing agent has a co-agent and 0 otherwise. Source: MLS
Dual_agent	The indicator variable equal 1 for listing agent is a dual agent and 0 otherwise. Source: MLS

Table 2.A

Summary - All variables

This table reports summary statistics for the key variables associated with completed transactions over the sample of Gwinnett County MLS sales data over 2004-2020. Columns 1, 2, and 3 present min, mean, and max values for all sold properties, respectively. The selling agent's volume variable is computed only using the transactions with non-missing selling agents.

	Number of Observations: 74591		
	Min	Mean	Max
	(1)	(2)	(3)
SP	40714.82	199463.51	621935.52
TOM	2	54.94	413
Listing Densiy	0	2.6847	15.8872
LnSQFT_TOT	1075	2433.2502	5956
lnAGE	2	18.6558	51
SHO_vacant	0	0.1006	1
lnBR	2	3.796	6
lnBAF	1	2.4332	5
lnBAH	0	0.5401	2
ATTACHED_TH	0	0.0529	1
FIREPLACE	0	1.0036	3
Brickframe	0	0.2388	1
Brick3sided	0	0.1543	1
Brick4sided	0	0.0633	1
Brickfront	0	0.1676	1
STO_onestory	0	0.2521	1
AMEN_neighborhoodassoc	0	0.4603	1
AMEN_park	0	0.0427	1
AMEN_playground	0	0.2789	1
AMEN_walkschool	0	0.0463	1
AMEN_golfcourse	0	0.0504	1
AMEN_gatedcommunities	0	0.0166	1
AMEN_clubhouse	0	0.1032	1
frac_below_18	0.14	0.2867	0.391
frac_65_over	0.004	0.0802	0.244
frac_bach_higher	0.069	0.3715	0.813
log_median_income	861	3015.4114	7559
INVESTOR_SELLER	0	0.1364	1
INVESTOR_BUYER	0	0.0294	1
NE_BLACK	0	0.1876	1
NE_ASIAN	0	0.0237	1
NE_HISP	0	0.0926	1

Table 2.A - Continued

LA_parttimer	0	0.189	1
LA_neighborhood	0	56.8961	20491
LA_age25below	0	0.1156	1
LA_age65plus	0	0.0033	1
LA_coagent	0	0.0507	1
DUAL_agent	0	0.1693	1
LA_farming	0	0.1202	1
LA_mkt_share	0	0.1821	1
SA_parttimer	0	0.0131	1
SA_neighborhood	0	0.3438	1
SA_age25below	0	8.6222	2418
SA_age65plus	0	0.0641	1

Table 3.A

Price-Liquidity SUR Model - All estimates for Different Diversity Measures

This table reports coefficient estimates from SUR regressions with the natural logarithm of selling price lnSP and natural logarithm of days on market lnTOM . (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)		(2)		(3)		(4)	
	lnSP	lnTOM	lnSP	lnTOM	lnSP	lnTOM	lnSP	lnTOM
Intercept	8.497***	2.7358***	8.3803***	2.7982***	8.1955***	2.7655***	8.1733***	2.7825***
	(263.1179)	(27.3462)	(258.7075)	(28.0291)	(261.1639)	(28.675)	(260.0296)	(28.8357)
Listing Density	-0.0022***	0.0074***	-0.0037***	0.0077***	-0.0041***	0.0075***	-0.0045***	0.0075***
	(-6.7021)	(7.2608)	(-11.3258)	(7.7309)	(-12.753)	(7.505)	(-13.9343)	(7.5507)
lnSQFT_TOT	0.4197***	0.1417***	0.4219***	0.1405***	0.4249***	0.1414***	0.426***	0.1412***
	(129.7287)	(14.1416)	(129.7239)	(14.016)	(130.4158)	(14.1238)	(130.6849)	(14.1073)
lnAGE	-0.1033***	0.0417***	-0.104***	0.0411***	-0.1016***	0.0416***	-0.1011***	0.0418***
	(-68.4401)	(8.9161)	(-68.3631)	(8.7632)	(-66.7928)	(8.9021)	(-66.3686)	(8.9395)
SHO_vacant	-0.0331***	0.0236***	-0.0325***	0.0236***	-0.0326***	0.0235***	-0.0327***	0.0235***
	(-13.6646)	(3.1449)	(-13.3502)	(3.1426)	(-13.3753)	(3.1366)	(-13.3796)	(3.1294)
lnBR	0.1409***	0.0138	0.1404***	0.0141	0.1401***	0.0136	0.1392***	0.0135
	(23.5975)	(0.7437)	(23.3938)	(0.763)	(23.2843)	(0.7364)	(23.1033)	(0.7291)
lnBAF	0.3715***	0.105***	0.3718***	0.1049***	0.3727***	0.1047***	0.3721***	0.1044***
	(67.6187)	(6.1711)	(67.3269)	(6.1661)	(67.3021)	(6.1534)	(67.1044)	(6.1329)
lnBAH	0.0994***	0.053***	0.1001***	0.0529***	0.1002***	0.0529***	0.1003***	0.0529***
	(39.9826)	(6.8872)	(40.06)	(6.8719)	(40.006)	(6.8755)	(39.9718)	(6.8693)
ATTACHED_TH	-0.2284***	-0.0023	-0.2285***	-0.001	-0.2349***	-0.0014	-0.2342***	-0.0017
	(-62.0788)	(-0.2049)	(-61.707)	(-0.0838)	(-63.3916)	(-0.1266)	(-63.1387)	(-0.1472)
FIREPLACE	0.0631***	0.006	0.0632***	0.0058	0.0638***	0.0058	0.0637***	0.0058
	(36.7118)	(1.1202)	(36.6091)	(1.0978)	(36.8402)	(1.0987)	(36.719)	(1.096)
Brickframe	0.0355***	0.0092*	0.0361***	0.0091*	0.036***	0.0093*	0.0363***	0.0093*
	(21.3724)	(1.7971)	(21.6621)	(1.7719)	(21.5025)	(1.8025)	(21.7019)	(1.8028)
Brick3sided	0.0283***	0.0089	0.0287***	0.0089	0.0286***	0.009	0.0289***	0.0089
	(14.0595)	(1.4323)	(14.187)	(1.4205)	(14.0726)	(1.4369)	(14.1876)	(1.424)
Brick4sided	0.09***	0.0421***	0.0899***	0.042***	0.0893***	0.0425***	0.0904***	0.0425***
	(29.4384)	(4.4511)	(29.2769)	(4.4372)	(28.9934)	(4.4832)	(29.3164)	(4.4885)
Brickfront	0.0157***	-0.0075	0.0144***	-0.0072	0.0137***	-0.0072	0.0137***	-0.0072
	(8.0994)	(-1.247)	(7.4179)	(-1.1944)	(7.0164)	(-1.2093)	(7.0127)	(-1.2066)
STO_onestory	0.0483***	-0.0218***	0.0484***	-0.022***	0.049***	-0.0219***	0.049***	-0.022***
	(24.1948)	(-3.5275)	(24.1314)	(-3.5512)	(24.3698)	(-3.5432)	(24.3188)	(-3.5507)
AMEN_neighborhoodassoc	0.0321***	-0.0037	0.034***	-0.0044	0.0347***	-0.0038	0.0357***	-0.0038
	(19.7854)	(-0.7429)	(20.8714)	(-0.8706)	(21.2351)	(-0.7561)	(21.8461)	(-0.7633)
AMEN_park	0.0238***	0.0212*	0.0236***	0.0207*	0.0258***	0.021*	0.0259***	0.0209*
	(6.7743)	(1.9506)	(6.6838)	(1.9023)	(7.2934)	(1.9307)	(7.3034)	(1.9204)
AMEN_playground	0.0087***	-0.0045	0.0083***	-0.0042	0.0079***	-0.0045	0.0075***	-0.0046
	(4.9206)	(-0.8169)	(4.689)	(-0.7725)	(4.4493)	(-0.8184)	(4.2171)	(-0.8357)
AMEN_walkschool	0.007**	-0.0217**	0.006*	-0.0217**	0.0063*	-0.0217**	0.0064*	-0.0216**
	(2.103)	(-2.1196)	(1.8159)	(-2.1171)	(1.8896)	(-2.1109)	(1.903)	(-2.1023)
AMEN_golfcourse	0.0633***	-0.0039	0.0675***	-0.0052	0.071***	-0.0048	0.071***	-0.005
	(19.6105)	(-0.3927)	(20.846)	(-0.5247)	(21.8922)	(-0.4833)	(21.8574)	(-0.4966)
AMEN_gatedcommunities	0.0964***	0.1404***	0.0927***	0.141***	0.0918***	0.141***	0.0919***	0.1415***
	(17.4344)	(8.1916)	(16.6703)	(8.228)	(16.458)	(8.2278)	(16.4648)	(8.2564)
AMEN_clubhouse	0.0435***	0.0231***	0.0425***	0.0225***	0.0456***	0.0229***	0.0455***	0.0229***
	(16.995)	(2.9123)	(16.5029)	(2.8334)	(17.6753)	(2.8803)	(17.621)	(2.8797)

Table 3.A - Continued

frac_below_18	-0.0405	-0.2324***	0.0199	-0.2638***	0.1156***	-0.2488***	0.1214***	-0.2458***
	(-1.4397)	(-2.6692)	(0.7045)	(-3.0321)	(4.1318)	(-2.8919)	(4.3312)	(-2.8566)
frac_65_over	0.0995***	0.1506	0.1513***	0.1243	0.1429***	0.1661	0.2329***	0.1593
	(2.9441)	(1.4379)	(4.4567)	(1.1882)	(4.1239)	(1.56)	(6.8067)	(1.5169)
frac_bach_higher	0.3863***	-0.0572*	0.4453***	-0.0711**	0.4372***	-0.0546*	0.4751***	-0.0654**
	(40.5817)	(-1.9382)	(47.6735)	(-2.4686)	(44.846)	(-1.8219)	(51.0892)	(-2.29)
log median_income	0.007***	0.012	0.0078***	0.0117	0.0097***	0.0114	0.0085***	0.0109
	(2.8202)	(1.5461)	(3.1045)	(1.5161)	(3.8655)	(1.4678)	(3.3791)	(1.4096)
Investor_seller	-0.1109***	0.0004	-0.1123***	0.0007	-0.1121***	0.0004	-0.1128***	0.0004
	(-49.5826)	(0.0618)	(-49.9974)	(0.1028)	(-49.7509)	(0.0607)	(-49.9965)	(0.0624)
Investor_buyer	-0.1335***	-0.1413***	-0.1329***	-0.1415***	-0.1322***	-0.1414***	-0.1322***	-0.1414***
	(-33.3002)	(-11.3735)	(-32.9723)	(-11.3914)	(-32.7262)	(-11.3854)	(-32.691)	(-11.3838)
NE_BLACK	-0.0592***	0.0062	-0.0594***	0.0077	-0.0578***	0.0043	-0.065***	0.0028
	(-24.4339)	(0.8273)	(-24.316)	(1.0254)	(-23.0207)	(0.5627)	(-25.3593)	(0.3506)
NE_ASIAN	0.0398***	0.014	0.038***	0.0177	0.0302***	0.0137	0.0242***	0.012
	(8.5071)	(0.9681)	(8.0494)	(1.2147)	(6.3944)	(0.9431)	(5.0861)	(0.8186)
NE_HISP	-0.014***	-0.0099	-0.0371***	-0.0097	-0.0114***	-0.0137	-0.0273***	-0.0086
	(-4.2992)	(-0.9852)	(-11.3235)	(-0.9561)	(-3.257)	(-1.2791)	(-8.3554)	(-0.8541)
LA_PARTTIMER	0.0064***	0.0395***	0.007***	0.0393***	0.0079***	0.0393***	0.0077***	0.0392***
	(2.7515)	(5.4728)	(2.9938)	(5.4412)	(3.3748)	(5.4422)	(3.2773)	(5.4347)
lnLA_VOL_2SIDES	-0.0046***	-0.0015	-0.005***	-0.0014	-0.0053***	-0.0015	-0.0053***	-0.0015
	(-7.8757)	(-0.8364)	(-8.455)	(-0.7745)	(-8.8984)	(-0.7997)	(-8.9245)	(-0.8048)
LA_neighborhood	0.0221***	0.004	0.022***	0.0039	0.0226***	0.004	0.0226***	0.004
	(9.8368)	(0.5823)	(9.7826)	(0.5623)	(9.9978)	(0.5746)	(10.0043)	(0.5696)
LA_age25below	-0.0065	-0.0396	-0.0099	-0.0387	-0.0117	-0.0392	-0.0123	-0.0392
	(-0.5545)	(-1.097)	(-0.8437)	(-1.0702)	(-0.9988)	(-1.0841)	(-1.0445)	(-1.0852)
LA_age65plus	0.0001	0.0323***	-0.0001	0.0323***	0	0.0324***	0.0001	0.0324***
	(0.0467)	(3.3665)	(-0.0206)	(3.3637)	(-0.0105)	(3.3726)	(0.0421)	(3.3763)
LA_coagent	0.0124***	-0.0158***	0.0127***	-0.016***	0.0132***	-0.0159***	0.0132***	-0.0159***
	(6.8868)	(-2.846)	(7.0225)	(-2.8758)	(7.3149)	(-2.8647)	(7.2982)	(-2.8657)
DUAL_agent	-0.0076***	0.0457***	-0.0081***	0.0458***	-0.0079***	0.0457***	-0.0081***	0.0457***
	(-3.242)	(6.3281)	(-3.4573)	(6.3379)	(-3.3557)	(6.3256)	(-3.4534)	(6.3254)
lnLA_farming	0.0298***	0.0369**	0.0313***	0.0364**	0.0329***	0.0365**	0.0326***	0.0364**
	(5.5819)	(2.2337)	(5.8272)	(2.2043)	(6.1218)	(2.208)	(6.0596)	(2.2022)
lnLA_dominance	0.2421***	-0.2064*	0.2632***	-0.217*	0.2983***	-0.213*	0.2974***	-0.2128*
	(6.259)	(-1.7229)	(6.7703)	(-1.8114)	(7.658)	(-1.7793)	(7.6262)	(-1.7771)
SA_PARTTIMER	0.003	0.0173***	0.0033*	0.0173***	0.0033*	0.0173***	0.0034*	0.0173***
	(1.604)	(2.9956)	(1.7339)	(2.9848)	(1.7539)	(2.993)	(1.798)	(2.9922)
lnSA_VOL_2SIDES	-0.0026***	-0.0103***	-0.0025***	-0.0104***	-0.0023***	-0.0104***	-0.0023***	-0.0103***
	(-3.7257)	(-4.8365)	(-3.5783)	(-4.8664)	(-3.3214)	(-4.8452)	(-3.2488)	(-4.836)
SA_neighborhood	0.0185***	0.0052	0.0194***	0.005	0.0199***	0.0051	0.0201***	0.005
	(6.5671)	(0.5996)	(6.8261)	(0.5677)	(7.0065)	(0.5867)	(7.072)	(0.5771)
SA_age25below	-0.0013	-0.0314	-0.0015	-0.031	-0.0027	-0.0313	-0.0029	-0.0314
	(-0.1433)	(-1.1441)	(-0.1723)	(-1.131)	(-0.2973)	(-1.1403)	(-0.3211)	(-1.1442)
SA_age65plus	0.011***	0.0328**	0.0102**	0.0329**	0.0097**	0.033**	0.01**	0.033**
	(2.646)	(2.5494)	(2.4362)	(2.5595)	(2.317)	(2.5661)	(2.3848)	(2.5684)
Selling quarter FE	yes	yes	yes	yes	yes	yes	yes	yes
ZIP code FE	yes	yes	yes	yes	yes	yes	yes	yes
Adj R-sq	0.8177	0.1127	0.8158	0.1126	0.8148	0.1127	0.8144	0.1127
Observations	74591		74591		74591		74591	