Place, Sustainability, and Urban Form as Revealed by U.S. Multi-Family Housing

Jeremy Gabe[A], Spenser Robinson[B], Drew Sanderford[C]

Abstract: Analysis of a large custom database describing U.S. multi-family buildings and their spatial contexts develops insight into the demand patterns for sustainable urban form, specifically consumer demand for density, design, distance to transit, land use diversity, and destination accessibility. The current era of substantial urban growth increases the importance of these demand factors as cities both contribute to and provide remedies for anthropogenic pollution. Consumers concurrently search for both an apartment and a neighborhood optimizing preferences among the two. Results indicate that consumers are willing to pay for residency in denser areas, with higher frequencies of transit service, that facilitate the use of a variety of transit modalities, and locations with greater accessibility to and from all other points in the city. Demand for more sustainable locations is evident though nuanced.

Keywords: Multi-family housing, sustainability, density, design, destination accessibility, transit

JEL Codes: R310, R320

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[A] Jeremy Gabe, University of Auckland, j.gabe@auckland.ac.nz
[B] Spenser Robinson, Central Michigan University, s.robinson@cmich.edu
[C] Drew Sanderford, University of Arizona, sanderford@email.arizona.edu

Introduction

Today, the majority of the world population resides in cities, where more than 70% of anthropogenic greenhouse gas emissions emanate (Kammen & Sunter 2017). Critically, cities can attenuate resource usage through their spatial structures (Glaeser & Kahn 2010) as well as perpetuate societal inequality (Saiz 2010). Changing development patterns and bid rent curves associated with urban population growth (Anas, Arnott, & Small 1998) alter relationships among individuals and firms (Hall 1995; Baumol 1968; Ioannides & Zabel 2007). Given increases in the demand for housing associated with urban population growth, multi-family housing stock rental choices can reveal consumer preferences, including those for more sustainable spatial structures in growing urban areas in the United States (U.S.). Using data from CoStar's Apartments.com and a variety of urban form measures identified by Ewing & Cervero (2010), this paper contributes to the conversation by identifying the demand for and economic competitive advantages created by attributes of sustainable urban form.

Although measuring sustainable urban form is a challenge, research from public health, transportation, and urban planning often uses five elemental clusters: density, diversity, design, destination access, and distance to transportation (Ewing & Cervero 2001 and 2010). Advancing this work, a variety of metrics describing and defining these clusters have been developed (Ewing et al 2003; Ramsey & Bell 2014). Research indicates that a number of these metrics are associated with positive outcomes such as reductions in vehicle miles traveled (Ewing & Cervero 2010) and lower morbidity and obesity (Ewing et al 2003). Further, they can help assess the location efficiency of low-income housing tax credit (LIHTC)-eligible projects (Adkins, Sanderford, & Pivo 2017).

These findings are complementary with urban economic analyses indicating that the dynamics of urban growth and urban design influence a range of phenomena including lending decisions (Avery, Beeson, & Sniderman 1999), access to transportation (Glaeser, Kahn, & Rappaport 2008), long-term outcomes for children (Chetty, Hindren, & Katz 2016), and crime (Gould-Ellen & O'Regan 2010). Shiller (2007) suggests that consumer concerns about pollution may, in the long-run, create demand for denser pedestrian friendly urban development. However, despite work defining sustainable urban form and analyses of urban growth related dynamics, demand for these attributes within growing urban places remains relatively under-explored.

In this context of urban growth and change, emerging techniques to measure components of sustainable urban form, connections between urban form and efficiency, and uncertainty about demand for urban sustainability, this paper considers the research question, *what does U.S. multi-family housing reveal about the consumer demand for specific aspects of sustainable urban form?* Its objectives are to use a national sample of multi-family apartment data to analyze sustainability and urban form demand signals in U.S. cities and to develop a systematic model of multi-family apartment rents that includes neighborhood sustainability characteristics. This second objective will also make a methodological contribution to the housing literature by potentially reducing upward bias identified in Bajari et al (2012), where unobserved neighborhood attributes are correlated with traditional hedonic model independent variables. Results from these analyses are likely to have implications for institutional investors seeking to allocate capital efficiently within the multi-family housing sector.

Below, section II describes the literature across several fields that inform the expectations and empirical models generated to advance the paper's objectives. Section III articulates the analysis data set which includes hedonic, economic, urban spatial structure, and other related characteristics drawn from private and public sources. Section III also summarizes the methods of analysis utilized. Section IV provides a discussion of the findings and limitations of the empirical models and Section V offers conclusion and identifies opportunities for future related research.

II. Background

From a finance and urban economics perspective, cities and urban spatial structure are key areas of study (e.g., Alonso 1968; Wheaton 1974; and Muth 1975; Wheaton 2004; Saiz 2010; Larson & Yezer 2015). Conversations in this literature about the drivers of urban land value (e.g., Hurd 1903 and Haig 1926) identify the role of accessibility within transportation networks (Alonso 1960) and the importance of site advantage or relative location (Wendt 1957). These concepts helped shape early research using hedonic applications and economic models attempting to parse the amenity/dis-amenity effects of mixing land uses (e.g., Kain & Quigley 1970 and Song & Knaap 2004). Related to this work, scholars have discerned unique bid rent curves for different patterns of growth (Anas, Arnott, & Small 1998), considered urban form and congestion issues (Wheaton 1998), and identified relationships between urban spatial structure and credit flows (Avery, Beeson, & Sniderman 1999).

As urban populations grow, agglomeration and related forces change the relationships between people, space, and firms which influence urban shapes, opportunities, and attractiveness (Glaeser 1992; Furman, Porter, & Stern 2002; Kline 2010). The interaction of growth and natural systems can lead to political and intergenerational conflict (Saiz 2010). Variation in air and water quality, impervious surface coverage, commuting patterns, and loss of habitat and prime soils for farmland all contribute to climate change and quality of life (Cervero 1998).

With expectations of more than 2.5 billion new urban residents (globally) in coming years (UN 2017), greater understanding about how cities grow and how residents consume space and housing has taken on new significance. For example, Ioannides & Zabel (2007) finds that individual housing consumption was linked to the housing consumption patterns of others within a neighborhood. This raises questions about the extent to which neighborhoods can be understood as substitutes or complements for one another (Ferreira & Gyourko 2012). Other work focuses on housing selection decisions. Geyer (2017) observes that households make simultaneous choices between which neighborhood they wish to live in and which home to buy—maximizing a utility function that satisfies both sets of constraints. These complex decisions have the potential to confound research using hedonic approaches as traditional model factors can correlate with unobserved neighborhood effects—upwardly biasing coefficient estimates (Bajari et al. 2012; Galiani, Murphy, & Pantano 2015).

As an illustration, economic research has difficulty separating out spatial characteristics from housing preferences associated with schools and crime. Collins & Kaplan (2017) reveal the upward bias of coefficients in school quality and home price analyses resulting from sorting behavior. Their results suggested that both data and econometric solutions can be used to separate the effects of housing and neighborhood choice. Adding additional perspective about the complexity of the housing-location decision, Laeven & Popov (2016) note that how and when households make education decisions influences home prices. In addition, homeowners are willing to pay higher prices to avoid locational dis-amenities. For example, households tend to be willing to pay more for housing spatially associated with lower crime rates (Bishop & Murphy 2011). Further, mixed use, high-density environments have been shown to lessen crime, suggesting that population density and urban design collaborate to create a lively and desirable place (Twinam 2017).

Households also tend to be willing to pay more for housing to live in proximity to transit system options (Bowes & Ihlanfeldt 2001; Duncan 2011; Hess & Almeida 2007; McMillen & McDonald 2004). Likewise, firms select office spaces in more transit-accessible locations (Nelson, Eskic, & Hamidi 2015). Beyond schools, crime and transit, the dynamics of urban growth and urban design influence a range of phenomena including urban lending decisions (Avery, Beeson, & Sniderman 1999), distributions of poverty given access to transportation (Glaeser, Kahn, & Rappaport 2008), long-term human capital outcomes for children (Chetty, Hindren, & Katz 2016), and crime (Gould-Ellen & O'Regan 2010).

The significance of urban spatial structure in prior research highlights an important limitation of hedonic techniques; that is, they can produce upwardly biased coefficients resulting from correlation with unmeasured but important information, such as qualitative "curb appeal" in real estate studies (Bajari et al 2012). Some have tried to solve this problem of correlated un-observables with quasi experimental designs (e.g., Chay & Greenstone 2005; Greenstone & Gallahger 2008). Others suggest using complex repeat sales methods to eliminate some of the correlation with un-observable attributes as well as identification timing issues (Bajari et al 2012). Alternatively, researchers have worked to generate models that separate neighborhood and housing attribute functions (Bishop & Murphy 2011).

Sustainability in the urban property market has been a research focus for some time. Eichholtz, Kok, & Quigley (2010) provide early financial economic analysis to identify price premiums associated with eco-labeled office buildings. Pivo & Fisher (2011) took a different approach. They drew on Ewing & Cervero (2001) and Ewing et al (2009) to identify the competitive advantage created by sustainable office buildings through the walkability of the places in which buildings were located. In this process, Pivo & Fisher (2011) demonstrate an early connection between sustainable commercial real estate and urban design. Subsequent work provides additional evidence, both with respect to equity and debt investment (e.g., Robinson & Sanderford 2016; Holtermans & Kok 2018; and An & Pivo 2018), to confirm that there is durable competitive advantage created by eco-labeled commercial buildings located in compact urban forms.

There is similar evidence for eco-certified homes and homes built with sustainable technologies. Supply of homes with eco-certifications and sustainable technologies is associated with climate, regional policy, and regional economic conditions (Sanderford, McCoy, & Keefe 2017). Like commercial buildings, homes built with sustainable technologies command price premiums (Dastrup et al 2012; Khan & Kok 2014; Kaza et al 2014). However, the evidence connecting housing to sustainable urban form is less robust and the signals are opaque. For example, there are single-market studies (Rauterkus, Thrall, & Hagnen 2010) and evidence from heavily regulated markets such as affordable multi-family housing (Pivo 2014) indicating that sustainable urban form is associated with reduced probability of mortgage default. Further, Bond & Devine (2015), found evidence that eco-certified and more walkable multi-family apartment buildings commanded price premiums.

Potentially conflicting with the directionality of this small evidence base, Freybote, Sun, & Yang (2015) studied residential condominium transactions in Portland, Oregon. They discovered that the eco-certifications at the "neighborhood scale" were not statistically associated with variation in condo prices. However, in agreement with Bond & Devine (2015), Freybote et al. did find eco-certifications for individual units associate with higher prices for those units. Importantly, their research belies the difficulty in dissociating spatial and building effects in regard to sustainability, a topic known to cross functional areas of study, investment practice, and management.

The real estate literature has explored relationships between apartment rents and the distance to central business district (Jaffe & Bussa 1975) as well as the distance to schools and shopping centers (DesRosiers, Theriault, & Menetier 1996), and other locational amenities associated with sustainable urban form (Valente, Wu, Gefand, & Sirmans 2005). However, measures of urban form are not solely described via a distance to housing unit measure. As a result, this raises questions around household demand for larger-scale sustainability of place in their housing decisions—especially as Freybote, Sun & Yang (2015) is one of only a few papers to investigate a direct measure of sustainable urban form, albeit an aggregated measure of urban form rather than its distinct components.

Critical to the effort of measuring urban form, research from planning, transportation, and public health has distilled out five component factors (the five D's) of sustainable urban form: density, diversity, design, destination accessibility, and distance to transit (Cervero & Ewing 2001; Jabareen 2006). These efforts describe the complexity and importance of measuring urban form (Wheeler & Beatley 2014) given recent re-urbanization and urban verticalization trends. Drawing on the initial work of Cervero and Ewing (2001) and Ewing et al (2003), researchers have found that more compact urban development patterns are associated with reductions in private vehicle miles traveled and reduced greenhouse gas emissions (Ewing & Cervero 2001; Ewing & Murakami 2010). There are also connections between auto-centric urban form and residential energy use (Ewing & Rong 2008). The literature goes on to note quality of life benefits via associations between sustainable urban form and individual obesity, cancer, and morbidity outcomes (Ewing et al 2003 and 2008). Further, density oriented regulations mitigate congestion and greenhouse gas emissions (Tiwari, Cervero, & Schipper 2011) as well as improve public health outcomes (Ewing et al 2008).

Recently, Ramsey & Bell (2014) generated dozens of empirical measures of sustainable urban form. Their work advanced specific metrics that capture and measure land use densities; land use and employment diversity; urban design and street network densities (auto/transit/pedestrian differentiated); transit availability, access, proximity, frequency, and density; and the accessibility of each place relative to all other places (Ramsey & Bell 2014). For example, given the relationship of housing-jobs-retail balances to urban commuting, congestion, emissions issues, and vibrancy (Peng 1997; Cervero & Duncan 2006), Ramsey & Bell (2014) introduced measures of residential land use density, employment densities across office, industrial, and retail job typologies at the Census Block Group (CBG) level. Denser CBGs tend to be more conducive to walking and transportation as well as to a diversity of a land uses and architectural types (Jacobs 1961; Jarabeen 2006). Ramsey & Bell (2014) advanced metrics of this development diversity by measuring road and intersection densities. Similar types of metrics are produced for employment diversity, location accessibility, and the other sustainability clusters.

Permitting significantly more depth to empirical investigation of demand for sustainable urban form, initial work using this new resource has utilized aggregations of urban form metrics to describe the location efficiency of LIHTC projects (Adkins, Sanderford, & Pivo 2017). However, these metrics have not been applied to analyses in the broader real estate markets to explore supply or demand signals relative to sustainable urban form.

III. Data & Methods of Analysis

This study begins by attempting to replicate prior related findings before examining the consumer demand for sustainable urban form revealed by multi-family housing. It then builds a series of econometric models assessing the demand for sustainable urban form revealed by the multi-family housing market using the literature summarized above and the results of the replication efforts.

A number of literature-based assumptions around rationality and sustainability drive the econometric models. This paper assumes that multifamily developers and renters are rational (Bajari et al 2012) and that renters seek to maximize their utility function where they rent the best bundle of apartment, complex, and neighborhood attributes (Geyer 2017). Additionally, the paper assumes that multifamily rents act as proxies for aggregate urban resident preferences. Combining those assumptions with recent multi-family oriented findings (Bond & Devine 2015) and the growing consistency within the real estate literature about the complex value proposition of sustainability, it further assumes sustainable building attributes are rational for renters/developers to consider. Finally, the paper assumes that urban design and spatial structure can be associated with consumer preferences (Avery, Beeson, & Sniderman 1999) and that neighborhood sorting can create endogeneity issues in econometric modeling (Galiani, Murphy, & Pantano 2015) that must be addressed with new techniques or data.

To examine the demand for sustainable urban design, the paper assembles an analysis data set of institutional-grade buildings from CoStar's Apartments.com and merges it with data describing urban form. The Apartments.com data describe two years of asking rent observations for more than 50,000 multi-family apartment buildings, representing activity across most of the largest 50 U.S. CBSAs by population.

In addition, data measuring urban form through density, diversity, design, destination access, and distance to transportation for this paper come from a range of public secondary sources including the Environmental Protection Agency, the Census Department, and the Centers for Disease Control. In some instances, custom variables were created using geographic information systems programs such as ArcMap or the "*sp*" package in *R*. The unit of analysis used is the multi-family complex which may be a single building or a related set of buildings in a complex.

Multi-Family Building Data

Rent observations include complexes with 50 or greater units covering the years 2016 and 2017. Freddie Mac categorizes complexes under 50 units as part of their "Small Balance Loan" portfolio; using larger complexes aligns the sample primarily to institutional class complexes. Complexes specifically designed for student housing, senior housing, or other specialty areas were excluded. Markets with 500+ building observations were initially included; though a few major markets such as Pittsburgh, San Francisco and Salt Lake City were also included having only 400+ building observations. A total of 51,147 unique building observations were available for analysis, most with year 2016 and 2017 rent records.

Control variables for quality, configuration type and age were constructed following guidance from industry standard practice and prior multi-family research (e.g., Sirmans, Sirmans, & Benjamin 1989; Guntermann & Norbin 1987; Benjamin, Chinloy, & Hardin 2007; Benjamin, Sirmans, & Zeitz 1997; and Hardin & Cheng 2003). Again, following Freddie Mac's definitions, "High Rise" buildings were categorized as those with 9 or greater floors and Garden-Style as those with 3 or fewer. Since the presence of an elevator was not observed, the omitted category includes "walk-up" and "mid-rise" which are partially distinguished by the presence of an elevator. CoStar's Apartment Rating, a 1-5 rating comparable to an "A", "B" or "C" class rating but with slightly more granularity was used as building level quality; these ratings take into account the physical condition of the building, services offered, and amenities on-site. Age of the building was as of 2017 and, although not shown in the descriptive analysis, evidence of a renovation within the last 10 years is controlled for in the regressions.

Rent observations are captured by Apartments.com on a daily basis. They use proprietary analytics to estimate monthly average asking rent per configuration. Their algorithms include accounting for multiple observations of the same unit, upcoming vacancies, and other data validity methods. Some are described by Florance et al (2016).

Based on these proprietary techniques, CoStar provided cleaned data in the form of monthly averages for this analysis. Those monthly averages were consolidated into two annual observations for 2016 and 2017 per building. Using full twelve months of each year tends to smooth out seasonality issues. Table 1 shows average rent per square foot (PSF) for each unique multi-family building, calculated as the weighted average per configuration type in Equation 1.

$$\text{Average Rent}_{it} = \frac{(\text{Studio Units}_i * \text{Studio Rent}_{it} + \text{1Bed Units}_i * \text{1 Bed Rent}_{it} + \text{2Bed Units}_i * \text{2 Bed Rent}_{it} + \text{3 Plus Bed Units}_i * \text{3 Plus Bed Rent}_{it})}{(\text{Studio Units}_i * \text{Avg Size}_i + \text{1Bed Units}_i * \text{Avg Size}_i + \text{2Bed Units}_i * \text{Avg Size}_i + \text{3 Plus Bed Units}_i * \text{Avg Size}_i)}$$

For complex *i* at time *t*.

National average rent was $1.44 PSF with highs in expected markets of New York and San Francisco at $4.00 PSF and $3.47 PSF respectively. Lows were observed in Cincinnati and Indianapolis at $0.87 PSF. As expected, the distribution of rents shows denser urban markets commanding higher PSF rents with Midwest cities and cities with available land earning lower PSF rents.

Include Table 1 about here

Additional Data Sources

Each of the apartment building records in the analysis dataset included latitude/longitude coordinates. Additional data were joined via these coordinates in one of two ways. First, using ArcMap, the latitude/longitude coordinates for each building were geocoded to reflect the location of the building relative to its Census Block Group (CBG). CBGs serve as the proxy for neighborhoods here following guidance from research (e.g., Gordon-Larsen, Nelson, Page, & Bopkin 2006) though additional models at the Census Tract were also tested. Data from the EPA's Smart Location Database (SLD) and U.S. Census' American Community Survey (ACS) were merged at the CBG. The EPA data provide detailed measures of the five D's of sustainable urban form: *density, diversity, design, distance to transit,* and *destination accessibility*. The ACS data specified a number of control variables.

Second, the latitude/longitude coordinates of the apartment buildings were used to generate new relative proximity metrics such as distance to or from various amenities (e.g., parks, transit stops, and coastline) described below. In these cases, ArcMap spatial relations tools were used to calculate Euclidian distances to features and amenities, except distance to coastline was derived using Euclidian distance calculated by the "sp" spatial analysis package for R between each building and the U.S. Census "coastline" shapefile in its TIGER database (which includes the Great Lakes, Pacific Ocean, Atlantic Ocean and Gulf of Mexico coastlines).

Smart Location Data

The analysis data set included all metrics from the Smart Location Database (SLD) with the exception of those generated from the General Transit Feed Specification (GTFS). The GTFS data is restricted by transit agency participation and created significant diminution of the sample. The SLD data is reported at the CBG and is clustered by the five D's. Multiple metrics are included in each cluster (Ramsey & Bell 2014). Table 2 describes, defines, and displays the sources of each metric used in the econometric models described below. Critically, the dataset does not include a central business district (CBD) measure. Instead, by metrics describing various aspects of human, built space, infrastructure, and employment activity, the entire dataset provides a finer grained set of replacements for traditionally coarse CBD boundaries.

Include Table 2 about here

Density measures include: residential density (housing units/acre), population density (people/acre), employment density (jobs/acre broken out across office, retail, industrial, service, healthcare, and entertainment categories), as well as a combination jobs + housing density metric. Considering of bid-rent theory, geographic constraints noted by Saiz (2010); land price issues in denser areas noted by Bostic, Longhofer, & Redfearn (2006); and default analysis by Pivo (2014), multi-family buildings located in denser areas are expected to command higher rents.

Diversity measures include: jobs-housing balance and intensity metrics across the same categories as well as trip generating estimates based on the employment diversities. Given findings about jobs-housing balance and employment-congestion from Peng (1997), Wheaton (1998), and Cervero & Duncan (2006), urban places that are more balanced tend to be more desirable and have fewer congestion issues. Buildings in these areas are likely to be desirable as they limit commuting and its attendant frustrations and externalities. As a result, diversity measures are expected to be positively associated with apartment rents—largely given the specification of the variables (e.g., closer to 1 = better as it illustrates balance).

Design measures describe the road and intersection densities: total road network density, network density across modalities (walking, transportation, automobiles) and intersection densities per square mile. Both road and intersection densities frame how friendly the urban form is to one or more types of users. Higher road and intersection densities promote walking and are less conducive to automobile use. Bond & Devine (2015) find that multi-family buildings earn greater rents in more walking friendly locations, thus transportation and pedestrian oriented design metrics are expected to be positively associated with apartment rents.

Distance or Access to Transportation measures include: distance to nearest transit stop (fixed guideway[1] only), the proportion of the CBG employment within ¼ and ½ mile buffers of transit stops, and the frequency of transit service in a CBG. Measures of household car ownership are also included. Based on results from John & Sirmans (1996), Rauterkus, Thrall, & Hagnen (2010) specific to car ownership; and Nelson, Eskic, & Hamidi (2015) as well as a range of multi-family literature noting distance to urban amenities (e.g., Jaffe & Bussa 1975; Sirmans, Sirmans, & Benjamin 1989; DesRosiers, Theriault, & Menetier 1996; Valente, Wu, Gefand, & Sirmans 2005), proximity to transit metrics should be negatively associated with apartment rents. As specified here using proportionate employment proximate to transit, both that association and the association of service frequency with rents is expected to be positive (reflecting the same phenomenon though measured differently).

Destination Accessibility measures included a range of accessibility indicators derived from a series of engineering and structural equation models that draw on transit patterns, trip generation matrices, employment, and housing patterns. Here, metrics describe how easy it is for a CBG to be accessed from all other CBGs by walking, transit, and private automobile. Walkability, for example, is a component of destination accessibility. Based on findings from Pivo & Fisher (2011) on walkability in commercial real

[1] "Fixed Guideway" transportation networks typically include heavy rail, light rail, and busways where buses have exclusive rights-of-way. These networks enjoy a competitive alternative to private vehicle transport as they are not affected by the same congestion that affects road transport infrastructure.

estate, Bond & Devine (2015) in apartments, and An & Pivo (2018) across asset classes, apartment buildings in more walkable places are expected to command higher rents than others without the locational advantage.

As parks are an important and occasionally controversial feature of cities for a number of reasons (Jacobs 1961), they were included in the analysis data set. Parks have been considered both amenities and dis-amenities over time (Hammer, Coughlin, & Horn 1974; Troy & Grove 2008; Sander & Polasky 2009). They provide and create public health, temperature/shade, ecosystem services, and physical activity benefits though also raise questions about environmental justice (Wolch, Byrne, & Newell 2014). Reflecting that debate, a comprehensive study of park access was conducted by researchers at the CDC in 2011 (Zhang, Lu, & Holt 2011). The CDC work quantified access to parks as the linear distance to each of the seven closest parks to the centroid of a CBG—ostensibly, the relativity of access. The measure was then population weighted (Zhang, Lu, & Holt 2011).

To test the robustness of that metric, a custom non-population weighted parks measure was generated from the ESRI USA Parks shapefile. Polygons describing the boundaries of local, regional, state, and national parks were mapped using ArcMap. Then, using geo-processing tools within ArcMap, the Euclidian distances (straight line) to each of four nearest parks was calculated. Though there is not consensus in the literature, the benefits of park access tend to be positively capitalized into home prices. Consequently, as these are distance measures, these variables are expected to present a negative relationship to apartment rents; buildings with lower distances and greater relative access should see greater rents *ceteris paribu*s.

Additional variables were added to the Diversity vector, including basic demography metrics describing neighborhood poverty, income, mean travel time to work, and education. The data were drawn from the Census' American Community survey. Each of these measures was captured at the Census Block Group level and extracted from the ACS 5-Year estimate files for 2011-15. Given the non-random geographical distribution of cities in the dataset, a quarter mile distance to coast metric was generated using the U.S. Census' TIGER File Boundary lines from all oceans and Great Lakes. Using a binary approach, if an apartment building was located within this buffer, it was coded as a one and if not a zero. The aim of the coastal control variable was to reduce potential correlation with other un-observed effects.

Correlation, Principal Component Analysis, & Variance Inflation Factors

The SLD contains numerous variables inherently correlated with each other given their measurement of urban development and urban economic phenomena. For example, macro variables like regional access to transit demonstrate high correlation to transit per square mile and transit within a quarter mile variables. Where these correlations existed one variable was selected to best represent that measurement.

Econometric methods primarily used for the analysis limit the ability to execute Variance Inflation Factor (VIF) testing. Variables for all models were selected using stepwise regressions and the examination of correlations both in the matrix and through VIF on comparable ordinary least squares (OLS) regressions. The highest impact variables with no known statistical (not necessarily actual) multicollinearity issues were selected into analytical models discussed below. Each model was checked for robustness across fixed and random effects specifications as well as propensity weighted and non-propensity weighted specifications using the propensity weighting approach of Eichholtz, Kok & Quigley (2010). No building attributes were meaningfully correlated. As a secondary multicollinearity test, ordinary least squares dummy variable regressions (OLSDV) replicated all models; all VIF results were below 10, excepting the intrinsically correlated natural log of building age and its squared term.

Econometric Approaches

Obvious differences between markets such as New York and Cincinnati require market level controls. This is especially true in the multi-family market (Wolverton, Hardin, & Cheng 2005). However, the heterogeneity within each geographic market suggests random effects as they control for market level differences but permit within market variation (Bell and Jones, 2016; Robinson et al., 2018; Seiler and Walden, 2014; Wooldridge, 2012).

Equation 2:

$$LnAvgRent_{ijt} = \beta_{0jt} + \beta_{1jt}\vec{A}_i + \beta_{2jt}\vec{D}_{1i} + \beta_{3jt}\vec{D}_{2i} + \beta_{4jt}\vec{D}_{3i} + \beta_{5jt}\vec{D}_{4i} + \beta_{6jt}\vec{D}_{5i} + \epsilon_{ijt}$$

Where $\vec{A}_i$ is a vector of apartment complex characteristics such as size and composition for complex *i*. $\vec{D}_{1i}$ through $\vec{D}_{5i}$ are the vectors of Density, Design, Destination Accessibility, Distance to Transit and Diversity. Random effects control for market *j* and time *t*; unobserved between and within effects are captured in ϵ_{ijt}. Model 1 served as the base model. It included only apartment complex attributes, $\vec{A}$. Models 2-6 add the base model attributes and then each of the variables under one of the five sustainable urban form clusters, $\vec{D}_{1-5}$ (e.g., all factors remaining to describe *design*). Model 7 included all variables (Table 4 & 5).

Replication of Prior Work

Before exploring the demand for various attributes of sustainable urban form, the team sought to reproduce a reasonable facsimile of prior findings that touched on sustainability in both building and locational form. To do so, Equation 1 was specified taking guidance from prior studies (Pivo & Fisher 2011 and Bond & Devine 2015) that examined the relationships between walkability, green buildings, and commercial real estate rents in both office and multi-family respectively. Though the Apartments.com dataset did not have the gross lease variable and the EPA's Walkability index was used in place of WalkScore, model coefficients were directionally and qualitatively similar to those in both studies. Here, apartment buildings with higher walkability and with green certifications command higher rents. Although not the focus of this study, replicated models of Bond & Devine (2015), including green eco-labels of LEED yielded comparable rental premiums. That our much larger sample supports their work helps validate both studies.

Additionally, drawing on the Smart Location and Neighborhood Pattern sections (the land development) as well as the Green Building sections (vertical development) of LEED for Neighborhood Development, Equation 1 was specified to reflect the required elements using analogous variables to the extent possible. When both green building and sustainable urban form metrics were included in this model, they each revealed significant coefficients with directionally expected signs (e.g., positive significant for green buildings). To be clear, these results neither directly confirm nor refute those of Freybote, Sun & Yang (2015) as the precise scores and attributes of the LEED ND neighborhood in which they conducted their analysis are not fully replicable using the analysis dataset here. However, from a qualitative standpoint, that the green building signs were significant alongside sustainable urban form provides a complementary finding suggesting greater justification for exploring sustainable urban form and developing insight into demand for it revealed by the market for multi-family housing.

Insert Table 3 (Bond & Devine Replication Results about here)

Broadly, the replication results are important for two reasons. First, they provide additional evidence that market participants demand and are willing to pay marginally greater prices for attributes of sustainable urban form, holding all other factors constant—including eco-certifications. Second, they provide larger sample ballast (via both N of buildings and geographies) that sustainability of location is also associated with multi-family rents. In the context of observations by Ewing & Cervero (2010) about the elements of sustainable urban form and Bajari et al (2012) on the potential for correlations with un-observed factors, it stands to reason that if walkability, an attribute of sustainable urban form, is a significant predictor of rents in a hedonic model, there might be other factors related to building location that could also be associated with rents. Consequently, in the broad context of growing urban populations and the ability of cities to both contribute to and attenuate anthropogenic pollution, exploring demand for attributes of sustainable urban form appear both empirically warranted and important.

IV. Results & Discussion

General Discussion

Based on the literature noted above, urban form and sustainability have been research foci for some time. This paper contributes newly to the conversation about growing and changing cities by intersecting the two concepts and using the real estate market as a vehicle for analysis. As a result, many of the findings relate conceptually to previous studies while also providing new insights about the nuanced demand for sustainable urban form as revealed by multi-family renters.

Consistent across the model specifications, the majority of the sustainable urban form attributes were significant predictors of variation in multi-family rents. Substantively, density, design, diversity, distance to transit, and destination accessibility each revealed signals about the desirability of sustainable urban form. Individual indicators generally align conceptually with findings from Geyer (2017) in that they illustrate ways that consumers satisfice when making the complex and concurrent decision about which apartment to rent in which neighborhood (Table 4). The prioritizing of accessibility is evident.

Include Table 4 about here

For example, walkability has largely been viewed as a highly desirable urban attribute. Indeed, in the models including only building attributes and destination access metrics—of which walkability is one, the walkability index presents as positive and significant. Likewise, when only design variables are present in the model, the presence of pedestrian-oriented design infrastructure (“links") presents as positive and significant. However, when all sustainable urban form factors are included in the full model (model 7), walkability fails to present significantly while the pedestrian-oriented infrastructure variable is marginally negative.

This finding suggests that walkability, when considered alone, is desirable but when more direct measures of urban design, such as the reported travel to work behavior of residents or accessibility across multiple modalities from all other places in the city is considered, walkability as an intangible concept may not be as desirable to multi-family renters. This finding in no way suggests that walkability is un-important to urban consumers. However, the result illustrates the complexity of pedestrian oriented design in urban places and points out the importance of measuring it across multiple metrics. More simply, perhaps the models reveal that the option of walking to work supersedes inclinations toward a generic “walkable” neighborhood in the order of consumer preferences; with the priority of access to work via walking trumping the walkability to other non-work places. In addition, Model 7 communicates that the provision of additional pedestrian infrastructure has no effect on apartment demand unless it has a measurable effect on resident behavior.

Broadly, these results are congruent with expectations informed by prior theory and evidence, though the findings suggest some important nuances and new considerations in addition to the walkability discussion above. With respect to density measured by employment densities across industrial clusters, multi-family buildings in employment dense neighborhoods commanded greater rents than those whose employment densities were oriented towards retail or government jobs. Consistent with expectations based on Glaeser & Kahn (2004) about the innovation and economic benefits of proximity in urban places, multi-family renters prefer greater residential and commercial densities. Given that these densities represent concentrations of individuals and firms, this preference for greater urban density is a key finding for both institutional investors and urban policy makers. Critically, where crowding and other negativedensity related externalities are not included in the models given subjectivity in measurement, we cannot comment about potential limits to the demand for density.

Importantly, these models do not contain a specific metric describing proximity to the 'central business district' (CBD). A CBD metric often acts as a proxy for the very measures studied in this analysis. Instead, these results suggest that a finer grained approach to measuring where economic activity (job density), destination accessibility and related measures may better articulate consumer preferences for urban form and location. As examples, a number of variables correlated to a CBD measured independently such as walkability, pedestrian links, and transit variables all reduce in economic and/or statistical impact when measured in concert, more jointly representing a CBD. This, along with other findings, suggests that CBD – or more precisely, access to the most desirable land in a city – may be well controlled by this data set. This differs substantively from prior urban economic literature where distance has been a primary indicator.

Model Results & Discussion

For the discussion below, the results described are based on non-propensity weighted random effects GMM models (Table 4) with Census Block Group level measurements for non-building related vectors.

The control variables all meet traditional expectations as well as being consistent in sign and magnitude. Higher building quality as measured by the CoStar rating is positively associated with rents, resulting in an approximately 10-15% increase in rent per square foot per additional rating point. Likewise, high rise apartments attract a premium while garden level apartments attract a discount relative to mid-rise buildings. The configuration percentages map a market with diminishing returns to apartment size, with rents per square foot highest in buildings with a high percentage of small studio apartments and lowest in buildings with a high percentage of 3-bedroom (or greater) configurations (the omitted benchmark category). Recently renovated apartments rent for approximately 3% more per square foot, all else equal. Rental rates decline as buildings age. More buildings in the same complex have a small, positive, effect on rent. Finally, buildings within a quarter mile of the coast rent for 3-5% more per square foot.

Of all the controls, building height is most affected by measures of urban form because classical bid-rent theory would suggest high rise apartments are only built in the most desirable parts of the city, thus in the absence of urban form metrics (or a CBD measure), building height instruments for location. Illustrating this, when urban form is measured in full (Model 7), the premiums for high rise apartments and discounts for garden level apartments both fall.

With respect to *density*, residential density was positively associated with rents as were commercial densities as measured by employment in a range of industrial classifications including office, industrial, service, and entertainment. Healthcare and public employment densities each presented negatively across specifications; healthcare could be due to negative externalities such as ambulance noise. Broadly, that each density measure was a significant predictor of variation in rents is consistent with work from Glaeser & Kahn (2004) and others that emphasized the importance of proximity between individuals and firms —the closer the better for facilitating innovation, opportunity, and activity. Additionally, greater density is associated with reduced congestion and as a result helps reduce greenhouse gas emissions (Wheaton 1998; Cervero & Duncan 2006). The results are also consistent with expectations developed from Kelly & Malizia (2017) who articulate the importance of vibrancy within cities. The density results illustrate the preference of renters for being proximate to areas of private economic activity or vibrancy.

Design measures offer the first clear instance of nuance through satisficing around sustainable urban form and location in the housing decision. Across all model specifications, access to parks was positively associated with multi-family rents; the negative coefficient reflects the further away from parks the lower the rent. For large urban apartment buildings, proximity to greenspace is a natural complement and is consistent with the income and education control variable results—echoing potential distributive justice warnings from the prior literature (Zhang, Lu, & Holt 2011.) Beyond parks, the urban design findings provide an illustration of the satisficing or tradeoffs made in the concurrent housing-neighborhood search. Pedestrian and multi-modal oriented design measures were each significant predictors of rents in models that included solely building attributes and density measures. However, in the full model including all other urban form metrics, these measures either changed signs or became statistically insignificant. These results suggest that, while consumers find value in these pedestrian oriented design factors, they may prioritize other factors such as proximity to employment and vibrancy over physical urban form attributes.

The design trade-offs are further contextualized by the findings relative to destination accessibility. Broadly, the more accessible a building was from other parts of the city, the greater the rents. This held across walking, biking, and automobile modalities. Importantly, accessibility was also prioritized relative to employment. As the percentage of residents who traveled fewer than 10 minutes to work increased, so did rents. These findings held across model specifications and into the full model where all factors were included. The exception to the story within this cluster is walkability. Within the model where only building attributes and destination accessibility metrics were included, walkability was both a positive and significant predictor of rents. However, is not a significant predictor at any level in the full model. While on the surface it may seem the full model (Model 7) finding is inconsistent with Bond & Devine (2015) in multi-family and Pivo & Fisher (2011) in office, who both found improved competitive advantage in more walkable areas, holistic analysis suggests – as described above – that renters value space where pedestrian infrastructure is used, not always where it is present. Overall, with the exception of park proximity, design variables have very little effect on rent in the wider context of urban form as coefficient parameters are very low.

Destination variables from the ACS measure existing resident transport choices; all else equal, as the share of residents walking or cycling to work increases, so do apartment rents. Again, it appears likely that observed *use* of cycling and walking infrastructure serves as a better indicator of urban location preferences when compared with the design variable solely measuring the provision of infrastructure. While automobile accessibility (Destination_CBG_RegAccess_Auto) acts as a positive amenity, increasing rents, its effect is mitigated by the much stronger negative effect for the relative measure of automobile accessibility (Destination_CBG_RegCntrlty_Auto). This means that automobile access is good but the exclusivity of automobile access, presumably at the cost of transport choice, is a dis-amenity. Rather than contradict earlier findings this reveals nuance to multi-family consumers' preferences. Other destination variables behave as expected. In the classic urban economic trade-off, longer commutes are associated with lower rents. Likewise, as the number of jobs accessible to the apartment increases, which occurs when one resides close to an economic activity hub, so do rents.

Distance to transit offers further evidence of satisficing. In the models where building attributes and distance to transit measures are the only vectors, being with ¼ mile of a transit stop was not a significant predictor of rents though being within a ½ mile was positively and significantly associated. This complex finding is broadly consistent with recent work by Nelson, Eskic, & Hamidi (2015) who found quadratic function relationships between office rents and distance to transit stops. In the full model, the ¼ mile variable turned negative though still insignificant and the ½ mile presented as insignificant. Complementing these findings, greater transit frequency near an apartment building, was positively associated with variation in rents. That frequency was positive and significant in all model specifications suggests that proximity to transit alone may not be as important as proximity with better service. This follows the narrative that consumers demonstrate their preference for accessible places with high use; transit services are only frequent when in high demand, else operators would scale back service. Again, provision of infrastructure (proximity to a stop) is not as important as its observed use (measured by frequency of service). Being able to move efficiently to locations across the city, particularly by observing existing modal choices, seems important to urban renters.

Measures of spatial diversity indicated a relatively consistent story that was congruent with expectations. The metrics described complex phenomena such as trip and employment equilibrium and entropy; these metrics assess the extent to which places offer greater jobs-housing balances and activities and how those balances relate to trip generation across modalities. The negative signs for both trip and employment equilibrium were expected given prior literature describing the relationship between jobs-housing balance and reduced vehicle miles traveled (e.g., Cervero & Ewing 2010). The signal from these metrics is supported by the positive employment entropy (employment mixture) finding and the employment density findings noted above. Here, it seems there is demand for more diverse activities in the local areas where consumers would live and a preference for co-location of jobs and housing.

Other diversity measures such as the level of education also presented consistent with expectations as higher levels of education were associated with higher rents. The percentage of low wage workers in a CBG means less ability to pay for housing services, leading to lower rents. Interestingly, the percentage of owner occupied homes when only measured with diversity measures appears as significantly negative. Presumably, a high percentage of owner occupied homes is found in larger suburban CBGs, thus in the absence of other measure of urban form, acts as a suburban/urban instrument. However, in the full model, where measures such as commuting distance and automobile accessibility better describe the shared costs and benefits of suburban living choices, the expected effect of owner-occupancy to identify the relative quality of neighborhoods appears and it becomes significantly positive.

V. Conclusions, Limitations, and Implications

As cities grow and absorb new residents, they offer both contribution to and attenuation of anthropogenic pollution. In this context and given the growing importance of multi-family housing as a vector through which to explore urban phenomena, a large database describing U.S. multi-family buildings and their spatial contexts was analyzed to develop insight into the demand patterns for these sustainability attributes. Before engaging in the exploration of the new, this paper replicated and generally reproduced, to the extent possible, findings from prior research using newer and broader datasets. The results from Bond & Devine (2015) held and helped to provide a useful framework for extension and further exploration. Beyond the results of Bond & Devine, in the concurrent spatial search for both an apartment and a neighborhood, our regression models indicate that consumers are willing to pay for buildings in denser areas, with higher frequencies of transit service, with existing use of varied transit modalities, and locations with greater relative accessibility from all other points in the city. Demand for more sustainable locations is evident and robust to multiple specifications.

The results also shed some light onto the nuanced and complex decision parameters associated with renting an apartment in an urban area. These findings have substantial implications for institutional investors—especially moving forward in a potentially fee and yield constrained economic cycle. The results suggest buying or developing well-located buildings can create economic advantages. Buying buildings near or in the midst of where economic activity is occurring could help capture higher rents. Future analyses could examine investors' abilities to create and capture value based on these attributes, strategically identifying locations where urban form attributes are not fully capitalized into prices. Similarly, locating transit stops with high service frequency offers advantages but results suggest potentially greater investor impact by assessing the quality and frequency of service as well as accessibility of the building from other points in the city. Critically, the results reveal how apartment consumers satisfice when confronted with multiple sustainable urban form attributes. For example, a generic measure of "walkability" can provide a useful proxy for where renters want to live. However, it seems that accessibility and proximity to economic activity better describe demand when existing mode choices are observed.

For urban policy, this study provides the insightful conclusion that infrastructure projects or regulations designed to improve urban sustainability may not alter urban use patterns alone. Frequency of use and optimally located infrastructure near employment density will have a greater impact, so planners must carefully consider the effect of infrastructure on use and access. The set of design variables that solely measures the provision of infrastructure were largely insignificant drivers of rents or had a very minor effect on rents. As mentioned above, private investors, developers, and tenants will rationally examine existing accessibility and use patterns as better determinants of demand, so incentives – such as reduced development levies or access to finance – may be needed to entice private partners into developing identified urban growth nodes that do not have existing patterns of high use or accessibility.

Though the paper worked to address the problems of hedonic models identified by Bajari et al (2012) by including both spatial and building characteristics, the results have natural limitations. First, the models are each specified using CBG level spatial metrics (both alone and aggregated to the CT level). In any event, the lesson from Bajari et al (2012) is well taken; that is, the economist cannot observe all factors that consumers can. Changing geographic focus levels permits new insight given the spatial nature of markets and rental decisions. Similarly, there is a second hypothesis that is difficult to disprove. This study's disaggregated attempt at measuring urban form may simply distribute a latent, less complex, urban location decision determinant, such as a simple proximity to the CBD variable or the size of a city, into urban form variables that best proxy these latent variables. However, the large sample size in this study helps overcome the inefficiency of estimating parameters to correlated exogenous variables, meaning that the variable in which this latent determinant arises is likely to be a better measure for investors to use when strategically deciding on short- to medium-term location decisions for their capital.

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Exhibits:

Table 1

Descriptive Statistics. This table shows descriptive statistics for the 2016-2017 national apartment complex sample. The N represents average unique building complexes per year with 93% of the sample including both year observations. Garden level is 3 stories and under while Highrise is 9 stories and greater. Studio, 1 Bed, 2 Bed and 3 Plus Bed are percentage of that unit type in the mean complex. Age is as of 2017

Market	N	AvgRent PSF	Garden Level	High-rise	Costar Apt Rating	Studio	1 Bed	2 Bed	3 Plus Bed	# of Buildings	Studio Size	1 Bed Size	2 Bed Size	3 Plus Bed	Age
National	*51,147*	*1.44*	*75%*	*7%*	*4.0*	*6%*	*40%*	*44%*	*9%*	*11*	*114*	*609*	*882*	*561*	*38*
Atlanta	1,935	0.95	85%	2%	3.9	1%	33%	52%	14%	16	50	666	1,058	899	32
Austin	829	1.32	91%	2%	3.9	4%	48%	40%	8%	14	80	649	968	612	26
Baltimore	752	1.34	72%	8%	3.9	4%	36%	49%	11%	14	103	658	925	666	42
Boston	1,194	2.02	51%	11%	4.1	7%	40%	46%	8%	7	159	637	890	494	46
Charlotte	743	0.95	91%	1%	3.9	2%	33%	50%	15%	15	62	613	974	848	27
Chicago	1,683	1.48	51%	19%	4.1	17%	42%	34%	7%	6	200	610	749	421	52
Cincinnati/Dayton	855	0.86	89%	3%	4.0	3%	34%	52%	12%	12	66	538	859	574	39
Cleveland	876	0.92	72%	8%	4.0	3%	39%	50%	8%	9	81	573	871	430	45
Columbus	790	0.90	94%	1%	3.9	3%	31%	58%	9%	18	54	512	941	453	32
Dallas/Ft Worth	2,922	1.10	92%	1%	3.9	3%	47%	42%	8%	16	72	662	975	636	32
Denver	1,099	1.46	71%	7%	4.0	5%	45%	43%	7%	10	121	643	913	544	31
Detroit	1,214	0.96	87%	5%	4.0	2%	41%	49%	7%	13	66	639	901	401	42
East Bay/Oakland	713	2.32	84%	1%	4.2	5%	42%	45%	8%	9	119	595	857	449	39
Hampton Roads	594	1.03	89%	2%	3.8	2%	25%	59%	14%	16	39	557	943	797	36
Hartford	463	1.28	78%	3%	4.1	7%	41%	45%	7%	10	122	601	832	427	52
Houston	2,407	1.07	91%	1%	3.8	2%	47%	42%	9%	16	57	672	995	702	31
Indianapolis	668	0.86	91%	2%	3.9	4%	36%	49%	12%	17	86	650	946	742	35
Inland Empire (California)	847	1.29	100%	0%	4.2	2%	29%	56%	13%	15	53	525	894	528	30
Kansas City	848	0.90	86%	5%	3.9	5%	39%	45%	11%	14	105	616	898	608	40
Las Vegas	722	0.96	95%	2%	4.0	5%	33%	50%	12%	20	55	607	929	730	27
Long Island (New York)	1,295	2.12	16%	11%	4.0	18%	48%	27%	7%	3	235	530	603	276	60
Los Angeles	2,728	2.09	74%	3%	4.2	15%	43%	36%	6%	5	210	606	800	370	43
Milwaukee/Madison	700	1.14	76%	6%	4.1	7%	38%	47%	8%	7	147	605	922	416	34
Minneapolis/St Paul	1,215	1.20	77%	4%	4.0	6%	43%	43%	8%	4	180	677	925	579	38
Nashville	629	1.03	91%	2%	3.9	2%	34%	51%	13%	14	50	603	959	766	29
New York City	1,372	4.02	0%	59%	4.2	21%	47%	23%	9%	1	243	458	542	414	66
Northern New Jersey	1,294	1.78	68%	10%	4.2	5%	50%	39%	6%	9	117	680	909	377	40
Orange County (California)	929	1.93	93%	0%	4.1	4%	40%	50%	6%	14	93	605	940	385	39
Orlando	837	1.05	93%	1%	4.0	2%	34%	48%	16%	18	54	613	971	846	27

Philadelphia	1,975	1.27	77%	7%	4.0	5%	41%	45%	9%	11	107	626	884	516	46
Phoenix	1,386	1.05	95%	1%	4.1	6%	38%	48%	8%	16	115	609	894	531	30
Pittsburgh	323	1.14	63%	14%	4.1	5%	42%	42%	11%	9	119	600	856	577	43
Portland	1,251	1.33	83%	3%	4.1	7%	31%	52%	10%	11	102	547	866	584	31
Raleigh/Durham	607	1.01	90%	1%	3.9	2%	36%	50%	13%	15	48	630	996	840	27
Sacramento	821	1.29	98%	0%	4.0	2%	36%	52%	10%	14	69	588	882	506	35
Salt Lake City	419	1.08	81%	1%	4.0	3%	31%	49%	17%	10	63	518	886	671	27
San Antonio	806	1.04	95%	1%	3.8	4%	46%	41%	10%	16	86	646	947	697	30
San Diego	1,064	1.76	91%	1%	4.2	4%	35%	50%	11%	11	82	547	872	480	34
San Francisco	420	3.52	38%	15%	4.1	22%	41%	28%	9%	5	251	584	689	428	47
Seattle/Puget Sound	1,631	1.74	65%	5%	4.1	10%	41%	41%	8%	9	172	621	855	477	32
South Bay/San Jose	616	2.67	83%	1%	4.1	8%	41%	42%	9%	10	137	629	898	569	35
South Florida	1,430	1.37	68%	14%	4.1	3%	37%	45%	14%	10	73	580	860	670	30
St. Louis	579	0.95	80%	8%	4.0	4%	37%	50%	9%	13	63	586	894	506	46
Tampa/St Petersburg	982	1.06	92%	2%	4.2	3%	38%	47%	12%	16	58	629	944	708	30
Washington, DC	2,047	1.86	51%	17%	3.8	8%	40%	42%	10%	10	185	657	911	650	41
West Michigan	505	0.90	93%	1%	4.0	2%	35%	52%	12%	12	61	607	915	548	36
Westchester/So	1,144	1.42	21%	12%	4.0	13%	49%	29%	9%	3	162	500	570	338	61

Table 2
This table identifies the source and brief definition of the five "D," *Density*, *Design*, *Destination Accessibility*, *Distance to Transit and Diversity*, variables used in this analysis.

Variable	Source	Definition
Density_CBG_Residential	EPA SLD	Gross residential density (HU/acre) on unprotected land
Density_Emp_Retail_8	EPA SLD	Gross retail (8-tier) employment density (jobs/acre) on unprotected land
Density_Emp_Office_8	EPA SLD	Gross office (8-tier) employment density (jobs/acre) on unprotected land
Density_Emp_Ind_8	EPA SLD	Gross industrial (8-tier) employment density (jobs/acre) on unprotected land
Density_Emp_Service_8	EPA SLD	Gross service (8-tier) employment density (jobs/acre) on unprotected land
Density_Emp_Ent_8	EPA SLD	Gross entertainment (8-tier) employment density (jobs/acre) on unprotected land
Density_Emp_Edu_8	EPA SLD	Gross education(8-tier) employment density (jobs/acre) on unprotected land
Density_Emp_Health_8	EPA SLD	Gross health care (8-tier) employment density (jobs/acre) on unprotected land
Density_Emp_Public_8	EPA SLD	Gross pu8blic (8-tier) employment density (jobs/acre) on unprotected land
Design_CBG_AutoLink	EPA SLD	Network density in terms of facility miles of auto-oriented links per square mile
Design_CBG_MultiLinks	EPA SLD	Network density in terms of facility miles of multi-modal links per square mile
Design_CBG_PedestrianLink	EPA SLD	Network density in terms of facility miles of pedestrian-oriented links per square mile
Design_CBG_IntersectionWeighted	EPA SLD	Street intersection density (weighted, auto-oriented intersections eliminated)
Design_CBG_AutoInstersection_PSM	EPA SLD	Intersection density in terms of auto-oriented intersections per square mile
Design_CBG_Multi3Leg_PSM	EPA SLD	Intersection density in terms of multi-modal intersections having three legs per square mile
Design_CBG_Multi4Leg_PSM	EPA SLD	Intersection density in terms of multi-modal intersections having four or more legs per square mile
Design_CBG_Ped3Leg_PSM	EPA SLD	Intersection density in terms of pedestrian-oriented intersections having three legs per square mile
Design_CBG_Ped4Leg_PSM	EPA SLD	Intersection density in terms of pedestrian-oriented intersections having four or more legs per square mile
Design_CBG_Park	GIS	Euclidean distance to nearest park polygon edge, derived using Near tool in ArcGIS
Design_Apartment_ParkAccess	CDC	*apartment data only. CDC-based park accessibility score. Processed with Spatial Join function in ArcGIS.
Destination_Emp_Bike	ACS Census	MEANS OF TRANSPORTATION TO WORK: Bicycle: Workers 16 years and over -- (Estimate)
Destination_Emp_Walk	ACS Census	MEANS OF TRANSPORTATION TO WORK: Walked: Workers 16 years and over -- (Estimate)
oDestination_CBG_Auto_Jobs45Min	EPA SLD	Jobs within 45 minutes auto travel time, timedecay (network travel time) weighted
Destination_CBG_RegAccess_Auto	EPA SLD	Proportional Accessibility to Regional Destinations - Auto: Working age population accessibility expressed as a ratio of total CBSA accessibility
Destination_CBG_RegCntrlty_Auto	EPA SLD	Regional Centrality Index – Auto: CBG D5ce score relative to max CBSA D5ce score
Destination_CBG_Walkability	EPA	Index from National Walkability data
Destination_Emp_45Minsplus	ACS Census	Derived from US Census Bureau's ACS data for all commute trips 45 minutes or longer in temporal duration

Destination_Emp_30_45Mins	ACS Census	Derived from US Census Bureau's ACS data for all commute trips of temporal duration between 30 and 45 minutes
Destination_Emp_10_30Mins	ACS Census	Derived from US Census Bureau's ACS data for all commute trips between 10 and 30 minutes in temporal duration
Destination_Emp_10Mins	ACS Census	Derived from US Census Bureau's ACS data for all commute trips up to 10 minutes in temporal duration
Distance_Emp_Trnst_QtrMile	EPA SLD	Proportion of CBG employment within ¼ mile of fixed-guideway transit stop
Distance_Emp_Trnst_HalfMile	EPA SLD	Proportion of CBG employment within ½ mile of fixed-guideway transit stop
Distance_CBG_TrnstFreq_PSM	EPA SLD	Aggregate frequency of transit service (D4c) per square mile
Diversity_CBG_Edu_College_Some	ACS Census	EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER: Some college, 1 or more years, no degree: Population 25 years and over -- (Estimate)
Diversity_CBG_Edu_College_Trade	ACS Census	EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER: Professional school degree: Population 25 years and over -- (Estimate)
Diversity_CBG_Edu_Bach_Assoc	ACS Census	Derived from US Census Bureau's ACS data for bachelor's and associates degrees received.
Diversity_CBG_Edu_Graduate	ACS Census	Derived from US Census Bureau's ACS data for graduate degrees received.
Diversity_CBG_Pop_Mean_Income	ACS Census	HOUSEHOLD INCOME IN THE PAST 12 MONTHS (IN 2015 INFLATION-ADJUSTED DOLLARS): Total: Households -- (Estimate)
Diversity_CBG_Owner_Occupied	ACS Census	TENURE: Owner occupied: Occupied housing units -- (Estimate)
Diversity_CBG_PercentLowWage	EPA SLD	% LowWageWk of total #workers in a CBG (home location), 2010
Diversity_Emp_JobsPerHousehold	EPA SLD	Jobs per household
Diversity_Emp_Entropy_8	EPA SLD	8-tier employment entropy (denominator set to observed employment types in the CBG)
Diversity_CBG_TripEquilibrium	EPA SLD	Trip productions and trip attractions equilibrium index; the closer to one, the more balanced the trip making
Diversity_Region_Emp_Diversity	EPA SLD	Regional Diversity. Standard calculation based on population and total employment: Deviation of CBG ratio of jobs/pop from regional average ratio of jobs/pop
Diversity_Region_Emp_WkrsPerJob	EPA SLD	Household Workers per Job, as compared to the region: Deviation of CBG ratio of household workers/job from regional average ratio of household workers/job
Diversity_Emp_WorkersPerJob	EPA SLD	Household Workers per Job, by CBG
Diversity_Emp_Equilibrium	EPA SLD	Household Workers per Job Equilibrium Index; the closer to one the more balanced the resident workers and jobs in the CBG.

Table 3:
Hedonic Regression Estimates of Observed ln(AvgRent/SF). This fixed effect multivariate regression has a dependent variable of the natural log of average rent per square foot for the apartment complex sample (see Equation 1). See Table 2 for definitions of other variables. The model is an OLS fixed effect regression with year and market as fixed effects intercept. The model replicates Bond and Devine (2015). ***, ** and * indicate significance at 99%. 95% and 90% levels, respectively. Standard errors are clustered at market level.

Variable	**Model 1**
Intercept	-0.338***
LEED	0.089***
Destination_CBG_Walkability	0.088***
garden_level	-0.121***
highrise	0.147***
percentstudio	0.697***
percent1bed	0.480***
percent2bed	0.257***
Renovated	0.038***
Ln_age	-0.141***
Ln_age_Squared	0.018***
Gym	0.115***
Pool	0.043***
Private_Outdoor_Space	0.016***
R-Squared	0.731
Model N	98,362
Time Fixed Effects	yes
Market Fixed Effects	yes

Table 4:
Hedonic Regression Estimates of Observed ln(AvgRent/SF). Each multivariate regression has a dependent variable of the natural log of average rent per square foot for the apartment complex sample (see Equation 1). See Table 2 for definitions of other variables. Each model is a GMM mixed effect regression with year and market as random effects on the intercept. Model (1) shows baseline results with only building level controls. Models (2-6) incorporate one vector of *Density, Design, Destination Accessibility, Distance to Transit and Diversity* respectively. Model 7 includes all five "D" vectors. ***, ** and * indicate significance at 99%. 95% and 90% levels, respectively. Standard errors are clustered at market level.

Variable	Model1	Model2	Model3	Model4	Model5	Model6	Model7
Intercept	-0.2848	-0.6275**	-0.2668	-1.8646**	-0.3661*	-0.0228	-1.1940**
garden_level	-0.1255***	-0.0730***	-0.0987***	-0.0643***	-0.0908***	-0.0907***	-0.0339***
Highrise	0.1602***	0.1166***	0.1459***	0.1249***	0.1439***	0.1274***	0.0950***
Apartment_Building_Rating	0.1343***	0.1260***	0.1328***	0.1203***	0.1328***	0.1056***	0.0988***
Percentstudio	0.5907***	0.5359***	0.5780***	0.5383***	0.5742***	0.5425***	0.5012***
percent1bed	0.4089***	0.3750***	0.4001***	0.3758***	0.4040***	0.3735***	0.3492***
percent2bed	0.1906***	0.1824***	0.1936***	0.1907***	0.2007***	0.1709***	0.1746***
Ren10	0.0253***	0.0267***	0.0251***	0.0252***	0.0249***	0.0310***	0.0318***
Lnage	-0.1371***	-0.1356***	-0.1245***	-0.1152***	-0.1229***	-0.1364***	-0.1154***
lnage2	0.0226***	0.0195***	0.0183***	0.0158***	0.0184***	0.0232***	0.0157***
Number_of_Buildings	0.0003***	0.0004***	0.0003***	0.0004***	0.0005***	0.0003***	0.0005***
Coast_QtrMile	0.0481***	0.0370***	0.0463***	0.0915***	0.0530***	0.0380***	0.0488***
Density_CBG_Residential		0.0341***					0.0157***
Density_Emp_Retail_8		-0.0046***					-0.0002
Density_Emp_Office_8		0.0054***					0.0027***
Density_Emp_Ind_8		0.0044***					0.0023***
Density_Emp_Service_8		0.0102***					0.0017***
Density_Emp_Ent_8		0.0060***					0.0048***
Density_Emp_Edu_8		0.0022***					0.0010***
Density_Emp_Health_8		-0.0023***					-0.0011***
Density_Emp_Public_8		-0.0070***					-0.0084***
Design_CBG_AutoLink			0.0008**				0.0003
Design_CBG_MultiLinks			0.0010*				0.0000
Design_CBG_PedestrianLink			0.0329***				-0.0033*
Design_CBG_IntersectionWeighted			0.0002				0.0010
Design_CBG_AutoInstersection_PSM			0.0005				-0.0007**
Design_CBG_Multi3Leg_PSM			-0.0008***				-0.0002
Design_CBG_Multi4Leg_PSM			0.0002				-0.0008***
Design_CBG_Ped3Leg_PSM			-0.0026***				-0.0002
Design_CBG_Ped4Leg_PSM			-0.0011***				-0.0004
Design_CBG_Park			-0.0001				-0.0008***
Design_Apartment_ParkAccess			-0.0424***				-0.0077***
Destination_Emp_Bike				0.0168***			0.0119***
Destination_Emp_Walk				0.0065***			0.0058***
Destination_CBG_Auto_Jobs45Min				0.1350***			0.0986***
Destination_CBG_RegAccess_Auto				0.0433***			0.0325***
Destination_CBG_RegCntrlty_Auto				-0.1596***			-0.1380***
Destination_CBG_Walkability				0.0180***			0.0016

Destination_Emp_45Minsplus				-0.0151***			-0.0112***
Destination_Emp_30_45Mins				-0.0077***			-0.0112***
Destination_Emp_10_30Mins				0.0195***			-0.0068***
Destination_Emp_10Mins				0.0080***			0.0027***
Distance_Emp_Trnst_QtrMile					0.0003		-0.0002
Distance_Emp_Trnst_HalfMile					0.0058***		0.0004
Distance_CBG_TrnstFreq_PSM					0.0067***		0.0012***
Diversity_CBG_Edu_College_Some						-0.0481***	-0.0352***
Diversity_CBG_Edu_College_Trade						0.0166***	0.0121***
Diversity_CBG_Edu_Bach_Assoc						0.0159***	0.0189***
Diversity_CBG_Edu_Graduate						0.0200***	0.0169***
Diversity_CBG_Owner_Occupied						-0.0081***	0.0047***
Diversity_CBG_PercentLowWage						-0.3883***	-0.3302***
Diversity_Emp_JobsPerHousehold						0.0000	0.0000
Diversity_Emp_Entropy_8						0.0081**	-0.0038
Diversity_CBG_TripEquilibrium						0.0013	-0.0079**
Diversity_Region_Emp_Diversity						0.0355***	-0.0031
Diversity_Region_Emp_WkrsPerJob						-0.0139**	-0.0116*
Diversity_Emp_WorkersPerJob						0.0001***	0.0001***
Diversity_Emp_Equilibrium						-0.0018	-0.0026
AIC	-7,471	-12,406	-10,110	-17,307	-9,836	-16,545	-24,500
SIC	-7,477	-12,412	-10,116	-17,313	-9,842	-16,551	-24,506
Model N	98,060	98,060	98,060	98,018	98,060	98,040	98,018
Time Random Effects	X	X	X	X	X	X	X
Market Random Effects	X	X	X	X	X	X	X

Table 5

Propensity Weighted Hedonic Regression Estimates of Observed ln(AvgRent/SF). Each multivariate regression has a dependent variable of the natural log of average rent per square foot for the apartment complex sample (see Equation 1). See Table 2for definitions of other variables. Each model is a GMM mixed effect regression with year and market as random effects on the intercept. Each model is propensity weighted by its likelihood of being a LEED building. Model (1) shows baseline results with only building level controls. Models (2-6) incorporate one vector of *Density, Design, Destination Accessibility, Distance to Transit and Diversity* respectively. Model 7 includes all five "D" vectors. ***, ** and * indicate significance at 99%. 95% and 90% levels, respectively. Standard errors are clustered at market level.

Variable	Model1	Model2	Model3	Model4	Model5	Model6	Model7
Intercept	-1.0066**	-1.4454**	-1.2701**	-3.6201***	-1.1320**	-0.8799***	-2.6161**
garden_level	-0.1116***	-0.0549***	-0.0858***	-0.0387***	-0.0774***	-0.1344***	-0.0110***
Highrise	0.1590***	0.0942***	0.1396***	0.0892***	0.1324***	0.2344***	0.0728***
Apartment_Building_Rating	0.2803***	0.2546***	0.2811***	0.2596***	0.2787***	0.2778***	0.2168***
Percentstudio	0.6683***	0.6042***	0.6443***	0.5670***	0.6504***	0.6862***	0.5309***
percent1bed	0.5033***	0.4601***	0.4864***	0.4433***	0.4849***	0.1979***	0.4124***
percent2bed	0.2289***	0.2576***	0.2503***	0.2510***	0.2464***	0.0144	0.2412***
Ren10	-0.0148***	-0.0148***	-0.0144***	-0.0131***	-0.0093*	-0.1125***	-0.0117***
Lnage	-0.1027***	-0.1089***	-0.1036***	-0.1171***	-0.1044***	-0.0715***	-0.1113***
lnage2	0.0121***	0.0107***	0.0116***	0.0157***	0.0119***	0.0127***	0.0117***
Number_of_Buildings	-0.0085***	-0.0027***	-0.0050***	-0.0023***	-0.0054***	-0.0160***	-0.0001
Coast_QtrMile	0.1141***	0.0619***	0.1160***	0.1226***	0.1071***	0.0580***	0.0587***
Density_CBG_Residential		0.0431***					0.0183***
Density_Emp_Retail_8		-0.0055***					-0.0043***
Density_Emp_Office_8		0.0076***					0.0029***
Density_Emp_Ind_8		0.0021***					0.0007
Density_Emp_Service_8		0.0154***					0.0096***
Density_Emp_Ent_8		0.0171***					0.0132***
Density_Emp_Edu_8		0.0010***					-0.0001
Density_Emp_Health_8		-0.0048***					-0.0043***
Density_Emp_Public_8		-0.0193***					-0.0168***
Design_CBG_AutoLink			-0.0011***				-0.0041***
Design_CBG_MultiLinks			-0.0043***				-0.0038***
Design_CBG_PedestrianLink			0.0608***				0.0046**
Design_CBG_IntersectionWeighted			0.0095***				0.0092***
Design_CBG_AutoInstersection_PSM			0.0006*				0.0013***
Design_CBG_Multi3Leg_PSM			0.0000				0.0004
Design_CBG_Multi4Leg_PSM			0.0024***				0.0009***
Design_CBG_Ped3Leg_PSM			-0.0031***				-0.0001
Design_CBG_Ped4Leg_PSM			-0.0084***				-0.0070***
Design_CBG_Park			0.0003				-0.0008**
Design_Apartment_ParkAccess			-0.0455***				-0.0092***
Destination_Emp_Bike				0.0137***			0.0147***
Destination_Emp_Walk				0.0169***			0.0117***
Destination_CBG_Auto_Jobs45Min				0.2296***			0.1660***
Destination_CBG_RegAccess_Auto				0.2393***			0.1843***
Destination_CBG_RegCntrlty_Auto				-0.2732***			-0.2511***
Destination_CBG_Walkability				0.0199***			-0.0207***

Destination_Emp_45Minsplus				-0.0279***			-0.0230***
Destination_Emp_30_45Mins				-0.0046***			-0.0135***
Destination_Emp_10_30Mins				0.0204***			-0.0185***
Destination_Emp_10Mins				0.0044***			-0.0008
Distance_Emp_Trnst_QtrMile					-0.0041***		-0.0005
Distance_Emp_Trnst_HalfMile					0.0059***		-0.0024***
Distance_CBG_TrnstFreq_PSM					0.0127***		0.0024***
Diversity_CBG_Edu_College_Some						-0.0682***	-0.0250***
Diversity_CBG_Edu_College_Trade						0.0256***	0.0201***
Diversity_CBG_Edu_Bach_Assoc						0.0675***	0.0072***
Diversity_CBG_Edu_Graduate						0.0459***	0.0330***
Diversity_CBG_Owner_Occupied						-0.0322***	0.0028***
Diversity_CBG_PercentLowWage						-0.2928***	-0.1562***
Diversity_Emp_JobsPerHousehold						0.0000***	0.0000**
Diversity_Emp_Entropy_8						-0.0222***	0.0098*
Diversity_CBG_TripEquilibrium						0.0112	-0.0563***
Diversity_Region_Emp_Diversity						-0.0085*	0.0230***
Diversity_Region_Emp_WkrsPerJob						0.2067***	0.0661***
Diversity_Emp_WorkersPerJob						-0.0002*	-0.0006***
Diversity_Emp_Equilibrium						-0.1785***	-0.0554***
AIC	335,731	324,635	331,993	323,856	332,377	407,242	312,083
SIC	335,725	324,629	331,987	323,850	332,371	407,252	312,077
Model N	98,060	98,060	98,060	98,018	98,060	98,040	98,018
Time Random Effects	X	X	X	X	X	X	X
Market Random Effects	X	X	X	X	X	X	X

Appendix:

Appendix Table 1 Density Means. This Table shows sample means for variables from the EPA SLD and ACS census along with some custom made variables for "D" vector defined in the title. Variable definitions may be found in Paper Table 2. * indicates that the regressions in the paper use the natural log of this variable. † indicates that a scalar adjustment of 1,000 multiplication was made prior to natural log to ensure all variables were positive sign.

Market_Name	Density_CBG_Residential*†	Density_Emp_Edu_8*†	Density_Emp_Ent_8*†	Density_Emp_Health_8*†	Density_Emp_Ind_8*†	Density_Emp_Office_8*†	Density_Emp_Public_8*†	Density_Emp_Retail_8*†	Density_Emp_Service_8*†
National	11.74	1.06	1.75	1.98	1.40	2.91	1.04	1.10	3.51
Atlanta	3.64	0.30	0.61	0.68	0.67	1.04	0.33	0.41	1.21
Austin	4.13	2.51	1.00	0.68	0.91	0.75	1.01	0.52	1.23
Baltimore	7.74	1.87	1.07	2.07	1.19	1.58	2.29	0.71	2.34
Boston	10.74	1.46	2.05	2.93	2.40	4.35	1.56	1.37	3.49
Charlotte	2.43	0.19	0.52	0.75	0.50	1.27	0.27	0.35	1.35
Chicago	24.88	2.56	3.37	2.87	1.68	4.43	1.20	1.63	7.06
Cincinnati/Dayton	3.31	0.22	0.62	0.84	0.62	1.50	0.46	0.37	1.31
Cleveland	4.53	0.60	0.68	0.83	0.68	0.88	0.33	0.37	1.24
Columbus	3.74	0.28	0.53	0.66	0.48	0.86	0.73	0.47	0.96
Dallas/Ft Worth	6.24	0.55	0.78	0.73	0.95	1.30	0.32	0.60	1.58
Denver	6.98	2.26	1.24	1.60	1.15	2.40	1.40	0.77	2.80
Detroit	4.28	0.25	0.56	1.21	0.52	0.53	0.32	0.45	0.95
East Bay/Oakland	9.05	0.93	0.98	1.57	1.42	1.32	2.66	0.86	2.46
Hampton Roads	4.05	0.48	0.67	0.53	0.54	0.70	0.25	0.56	0.95
Hartford	4.25	0.51	0.87	0.92	0.84	3.95	0.71	0.35	2.47
Houston	5.38	0.96	0.72	0.88	1.53	0.92	0.34	0.71	1.62
Indianapolis	3.19	0.42	0.52	0.68	0.52	0.83	0.77	0.39	1.19
Inland Empire (California)	4.23	0.38	0.41	0.51	0.43	0.21	0.14	0.51	0.63
Kansas City	3.61	0.50	0.87	0.71	0.50	2.28	0.41	0.46	1.63
Las Vegas	7.78	0.54	1.21	0.56	0.40	0.49	0.16	0.52	0.74
Long Island (New York)	38.29	0.84	1.29	6.51	4.45	2.65	2.69	2.15	3.49
Los Angeles	15.09	2.26	2.01	1.78	1.58	2.66	0.68	1.42	3.96
Milwaukee/Madison	6.00	0.40	1.43	1.59	0.90	2.15	0.60	0.57	1.72
Minneapolis/St Paul	6.97	0.68	1.63	1.78	1.33	3.39	0.92	0.79	2.77
Nashville	2.54	0.40	0.65	0.74	0.53	0.73	1.13	0.34	0.85
New York City	109.29	6.32	21.07	17.02	10.09	45.81	6.49	11.15	43.35
Northern New Jersey	9.54	1.25	0.72	2.20	1.32	2.54	0.74	0.72	1.87
Orange County (California)	7.12	0.51	0.91	0.88	1.16	0.72	0.30	0.77	1.37
Orlando	3.37	0.24	0.54	0.37	0.41	0.48	0.44	0.38	0.85

Philadelphia	7.51	1.25	1.87	2.87	1.07	2.69	1.56	0.84	3.37
Phoenix	6.26	0.69	0.70	0.96	0.85	0.75	0.39	0.63	1.37
Pittsburgh	5.63	1.27	1.21	1.96	1.09	3.85	0.36	0.81	2.47
Portland	6.05	0.62	1.15	1.37	1.07	1.80	0.57	0.93	1.86
Raleigh/Durham	2.65	0.20	0.46	0.67	0.35	0.56	2.36	0.37	0.90
Sacramento	5.20	0.33	0.52	0.61	0.36	0.50	1.08	0.50	0.96
Salt Lake City	3.92	0.38	0.91	0.63	0.87	1.39	0.59	0.93	1.40
San Antonio	3.90	0.66	0.61	1.16	0.54	0.74	0.16	0.50	0.74
San Diego	7.76	0.52	1.22	0.94	0.78	0.63	1.00	0.72	1.61
San Francisco	30.66	1.14	9.01	4.24	3.10	6.92	3.32	2.64	10.84
Seattle/Puget Sound	10.62	1.23	2.41	3.03	2.67	3.37	1.48	1.66	6.08
South Bay/San Jose	8.07	0.39	1.04	0.72	1.49	0.87	0.20	0.78	1.86
South Florida	10.33	1.32	1.20	0.90	0.98	1.22	1.45	0.79	2.00
St. Louis	4.74	0.28	1.44	2.51	0.90	1.24	0.25	0.48	1.90
Tampa/St Petersburg	4.43	0.44	0.47	0.70	0.40	0.63	0.41	0.38	0.78
Washington, DC	13.48	0.97	2.14	1.31	1.05	2.08	1.80	1.19	6.75
West Michigan	2.59	0.32	0.44	2.34	0.66	0.40	0.29	0.30	0.63
Westchester/So Connecticut	34.21	0.65	1.04	3.93	1.54	1.94	0.77	1.55	2.29

Appendix Table 2 Design Means. This Table shows sample means for variables from the EPA SLD and ACS census along with some custom made variables for “D” vector defined in the title. Variable definitions may be found in Paper Table 2. * indicates that the regressions in the paper use the natural log of this variable. † indicates that a scalar adjustment of 1,000 multiplication was made prior to natural log to ensure all variables were positive sign.

Market_Name	**Design_Apartment_ParkAccess*†**	**Design_CBG_AutoInstersection_PSM*†**	**Design_CBG_AutoLink*†**	**Design_CBG_IntersectionWeighted*†**	**Design_CBG_Multi3Leg_PSM*†**	**Design_CBG_Multi4Leg_PSM*†**	**Design_CBG_MultiLinks*†**	**Design_CBG_Park*†**	**Design_CBG_Ped3Leg_PSM*†**	**Design_CBG_Ped4Leg_PSM*†**	**Design_CBG_PedestrianLink*†**
National	1.71	2.91	2.02	79.06	14.49	9.55	3.17	1,085	60.38	19.56	13.40
Atlanta	2.15	2.53	1.93	53.87	13.97	4.13	2.34	1,754	50.40	6.81	9.92
Austin	1.58	4.10	2.90	55.96	8.45	3.78	1.89	1,343	51.34	12.31	10.31
Baltimore	1.27	2.26	1.47	99.44	21.11	17.03	4.74	842	69.76	21.80	14.07
Boston	1.38	3.10	1.80	96.57	31.75	12.26	4.33	1,013	72.52	14.77	13.62
Charlotte	3.33	1.86	1.61	48.89	9.67	3.77	1.81	2,305	44.56	8.95	9.52
Chicago	0.89	1.81	1.05	93.74	15.01	13.36	3.24	432	64.96	27.04	15.15
Cincinnati/Dayton	2.19	1.85	1.41	54.80	14.72	5.32	2.70	1,094	43.41	10.71	9.63
Cleveland	2.38	1.59	1.20	55.02	15.11	5.44	2.50	1,536	43.04	10.79	9.96
Columbus	1.78	2.06	1.80	64.75	14.53	5.15	2.58	949	57.79	11.36	10.66
Dallas/Ft Worth	1.26	4.10	2.78	69.47	11.23	8.29	3.83	991	59.14	14.25	12.01
Denver	0.86	2.35	1.51	90.51	9.10	8.01	2.97	664	72.04	28.38	14.21
Detroit	1.67	2.88	1.70	63.61	15.48	4.56	2.46	1,024	50.81	14.84	11.61
East Bay/Oakland	0.76	2.81	1.70	97.57	18.39	11.94	3.74	480	76.97	22.03	14.79
Hampton Roads	1.95	2.76	2.60	72.74	10.14	5.59	2.00	1,453	62.85	18.47	12.63
Hartford	1.71	1.78	1.34	49.12	17.97	4.74	2.61	1,173	37.25	7.56	9.13
Houston	2.17	3.10	2.30	55.75	8.10	7.23	3.23	1,616	43.99	13.78	10.88
Indianapolis	2.52	2.02	1.80	64.72	9.08	4.98	1.97	1,609	56.65	15.90	11.85
Inland Empire (California)	1.51	1.58	1.58	61.52	12.01	6.80	2.61	983	55.28	9.83	11.05
Kansas City	2.62	2.79	2.13	78.38	14.17	8.33	2.59	950	62.92	18.63	12.70
Las Vegas	1.88	2.54	2.12	72.18	11.91	5.89	2.68	1,241	68.62	12.58	11.64
Long Island (New	1.28	2.69	1.42	96.92	17.25	17.32	4.38	855	47.72	36.27	20.88
Los Angeles	0.93	2.75	1.68	94.03	22.52	18.45	4.56	666	55.65	23.45	14.13
Milwaukee/Madison	1.27	2.26	1.44	68.71	10.00	10.43	3.37	769	46.02	20.92	11.32
Minneapolis/St Paul	2.31	4.38	3.17	82.12	9.95	8.35	2.87	657	64.32	24.23	13.19
Nashville	3.56	1.94	1.42	56.21	11.66	4.67	2.18	2,037	48.47	11.43	9.81
New York City	0.75	9.47	5.08	88.07	4.91	20.59	4.05	326	41.14	36.76	22.52
Northern New Jersey	1.66	2.41	1.59	75.25	21.88	9.64	3.28	1,045	50.18	17.55	13.06

Orange County (California)	0.76	4.12	3.70	83.99	17.21	7.74	3.55	561	79.46	11.77	12.75
Orlando	3.65	1.98	2.30	55.14	7.31	3.42	1.70	2,916	54.03	10.81	11.36
Philadelphia	3.81	1.69	1.12	82.18	14.10	8.36	2.67	2,031	59.35	24.82	14.18
Phoenix	1.55	1.87	1.87	91.41	13.37	6.23	2.60	921	90.70	15.76	15.03
Pittsburgh	2.30	2.64	1.14	87.08	20.66	8.74	3.16	1,516	62.10	23.14	13.59
Portland	0.91	2.51	1.76	109.95	18.33	9.84	2.80	687	81.19	33.73	15.84
Raleigh/Durham	2.09	2.11	1.87	52.34	10.94	4.27	2.03	1,621	47.73	8.94	9.36
Sacramento	2.22	2.16	1.84	71.53	13.62	6.27	2.84	775	64.70	13.03	12.27
Salt Lake City	1.80	1.63	1.46	69.30	16.10	6.54	2.64	1,208	58.82	12.79	11.83
San Antonio	2.18	3.09	2.19	51.88	10.60	4.08	2.16	1,747	44.15	11.28	10.43
San Diego	1.08	3.60	2.69	78.25	10.79	8.23	3.01	706	69.20	16.67	13.19
San Francisco	0.62	5.30	2.90	139.54	18.12	24.91	6.11	349	97.25	37.68	18.22
Seattle/Puget Sound	0.79	3.53	2.12	131.86	17.57	15.52	3.36	587	91.85	43.35	17.35
South Bay/San Jose	0.93	5.17	3.05	101.59	18.66	10.73	4.38	561	92.88	16.46	14.44
South Florida	1.33	2.48	2.38	92.66	12.58	9.11	2.98	1,075	76.06	24.43	15.89
St. Louis	1.28	2.43	1.47	75.71	12.54	6.20	2.18	936	59.78	21.27	13.51
Tampa/St Petersburg	2.57	2.00	2.24	74.99	9.48	5.14	1.71	1,640	71.09	16.11	13.64
Washington, DC	1.34	3.45	2.01	84.77	14.06	13.20	3.85	832	62.05	20.81	13.95
West Michigan	5.20	1.41	1.22	46.68	11.66	3.58	2.05	1,892	36.65	10.87	8.87
Westchester/So	0.94	2.97	1.76	91.33	25.65	17.94	5.36	497	45.66	25.82	17.68

Appendix Table 3 Destination Means. This Table shows sample means for variables from the EPA SLD and ACS census along with some custom made variables for "D" vector defined in the title. Variable definitions may be found in Paper Table 2. * indicates that the regressions in the paper use the natural log of this variable. † indicates that a scalar adjustment of 1,000 multiplication was made prior to natural log to ensure all variables were positive sign.

Market_Name	Destination_CBG_Auto_Jobs45Min*	Destination_CBG_RegAccess_Auto	Destination_CBG_RegCntrlty_Auto	Destination_CBG_Walkability*	Destination_Emp_10_30Mins*	Destination_Emp_10Mins*	Destination_Emp_30_45Mins*	Destination_Emp_45Minsplus*	Destination_Emp_Bike*
National	233,991	0.10	0.66	11.77	491	99	219	161	8.85
Atlanta	173,175	0.10	0.64	10.04	546	102	263	202	3.48
Austin	146,718	0.12	0.75	11.48	717	153	269	148	14.36
Baltimore	156,655	0.05	0.65	12.74	432	74	214	187	3.92
Boston	179,327	0.07	0.58	12.76	375	85	194	177	7.33
Charlotte	94,849	0.28	0.70	8.11	527	122	213	111	1.73
Chicago	274,951	0.03	0.54	12.64	389	76	209	201	10.69
Cincinnati/Dayton	95,328	0.11	0.68	9.86	462	107	150	69	1.85
Cleveland	96,154	0.19	0.69	9.73	434	108	165	87	3.15
Columbus	128,959	0.08	0.67	11.09	635	123	220	79	4.65
Dallas/Ft Worth	245,142	0.04	0.68	11.27	484	112	217	132	2.37
Denver	169,513	0.15	0.76	13.06	522	114	212	127	20.53
Detroit	141,032	0.10	0.66	9.30	351	81	141	90	3.74
East Bay/Oakland	196,744	0.03	0.62	13.20	371	75	195	258	11.97
Hampton Roads	74,142	0.09	0.65	11.84	529	99	176	83	4.05
Hartford	83,265	0.24	0.67	8.91	433	106	130	70	2.54
Houston	241,233	0.03	0.62	11.28	621	116	342	272	4.61
Indianapolis	102,771	0.17	0.66	10.68	583	146	246	116	6.77
Inland Empire	145,230	0.05	0.43	10.28	483	118	179	195	5.01
Kansas City	113,264	0.28	0.77	11.23	506	132	140	60	2.91
Las Vegas	184,536	0.08	0.79	12.36	500	78	180	74	4.65
Long Island (New York)	569,684	0.01	0.67	13.08	213	33	234	303	7.93
Los Angeles	501,703	0.02	0.53	13.81	463	87	256	221	11.56
Milwaukee/Madison	88,536	0.34	0.71	10.88	548	142	153	74	17.84
Minneapolis/St Paul	199,573	0.11	0.69	12.72	533	107	179	91	11.15
Nashville	82,769	0.28	0.65	7.70	632	123	249	162	3.42
New York City	1,086,447	0.01	0.88	13.91	424	68	319	195	15.21
Northern New Jersey	352,861	0.04	0.40	12.70	356	78	196	238	2.83
Orange County	444,810	0.01	0.44	13.78	572	99	227	164	13.53

Orlando	101,186	0.16	0.69	8.77	1,154	153	556	313	13.35
Philadelphia	144,961	0.18	0.62	12.25	418	97	160	135	5.3
Phoenix	217,385	0.04	0.77	9.11	436	92	169	87	13.52
Pittsburgh	100,336	0.06	0.57	12.09	349	79	152	103	4.85
Portland	113,771	0.23	0.70	13.71	507	130	175	115	23.72
Raleigh/Durham	110,905	0.30	0.77	11.23	779	159	217	111	8.59
Sacramento	119,975	0.13	0.69	12.03	422	101	159	93	20.81
Salt Lake City	111,819	0.27	0.76	13.81	635	154	184	97	12.04
San Antonio	129,089	0.08	0.74	7.87	617	120	205	104	3.03
San Diego	161,442	0.05	0.64	13.00	658	101	249	141	7.72
San Francisco	318,942	0.04	0.80	13.85	545	84	274	231	41.21
Seattle/Puget Sound	174,195	0.05	0.64	13.61	463	89	206	143	12.86
South Bay/San Jose	244,176	0.09	0.80	10.62	682	95	233	157	24.05
South Florida	164,830	0.03	0.66	12.68	455	70	249	159	6.88
St. Louis	135,589	0.06	0.70	12.23	491	92	181	86	3.18
Tampa/St Petersburg	97,796	0.10	0.71	11.96	469	93	181	106	7.15
Washington, DC	270,235	0.08	0.68	13.08	432	72	289	274	13.99
West Michigan	56,788	0.46	0.75	7.42	473	130	91	59	4.84
Westchester/So	400,275	0.06	0.67	12.03	234	54	130	213	3.24

Appendix Table 4 Distance Means. This Table shows sample means for variables from the EPA SLD and ACS census along with some custom made variables for "D" vector defined in the title. Variable definitions may be found in Paper Table 2. * indicates that the regressions in the paper use the natural log of this variable. † indicates that a scalar adjustment of 1,000 multiplication was made prior to natural log to ensure all variables were positive sign.

Market_Name	Distance_CBG_TrnstFreq_PSM*†	Distance_Emp_Trnst_HalfMile*†	Distance_Emp_Trnst_QtrMile*†
National	1,348	0.18	0.10
Atlanta	154	0.07	0.02
Austin	521	0.04	0.01
Baltimore	967	0.19	0.08
Boston	6,002	0.33	0.20
Charlotte	.	0.06	0.02
Chicago	4,457	0.45	0.25
Cincinnati/Dayton	331	0.00	0.00
Cleveland	284	0.11	0.06
Columbus	290	0.00	0.00
Dallas/Ft Worth	260	0.10	0.04
Denver	539	0.11	0.05
Detroit	340	0.02	0.01
East Bay/Oakland	660	0.20	0.07
Hampton Roads	86	0.04	0.02
Hartford	102	0.00	0.00
Houston	273	0.02	0.01
Indianapolis	281	0.00	0.00
Inland Empire (California)	316	0.02	0.00
Kansas City	493	0.10	0.06
Las Vegas	163	0.12	0.06
Long Island (New York)	3,221	0.76	0.46
Los Angeles	2,486	0.22	0.07
Milwaukee/Madison	735	0.02	0.01
Minneapolis/St Paul	1,902	0.05	0.02
Nashville	0	0.01	0.00
New York City	6,515	0.95	0.73
Northern New Jersey	1,170	0.26	0.10
Orange County (California)	217	0.02	0.01
Orlando	10	0.00	0.00
Philadelphia	1,662	0.23	0.13

Phoenix	0	0.08	0.03
Pittsburgh	1,205	0.18	0.08
Portland	1,484	0.22	0.13
Raleigh/Durham	123	0.00	0.00
Sacramento	263	0.07	0.03
Salt Lake City	591	0.21	0.08
San Antonio	.	0.00	0.00
San Diego	377	0.17	0.07
San Francisco	7,406	0.59	0.35
Seattle/Puget Sound	1,506	0.13	0.05
South Bay/San Jose	26	0.30	0.11
South Florida	678	0.10	0.05
St. Louis	486	0.13	0.05
Tampa/St Petersburg	247	0.02	0.01
Washington, DC	1,924	0.31	0.11
West Michigan	66	0.00	0.00
Westchester/So Connecticut	1,202	0.62	0.39

Appendix Table 5 Diversity Means. This Table shows sample means for variables from the EPA SLD and ACS census along with some custom made variables for "D" vector defined in the title. Variable definitions may be found in Paper Table 2. * indicates that the regressions in the paper use the natural log of this variable. † indicates that a scalar adjustment of 1,000 multiplication was made prior to natural log to ensure all variables were positive sign.

Market_Name	Diversity_CBG_Edu_Bach_Assoc*	Diversity_CBG_Edu_College_Some*	Diversity_CBG_Edu_College_Trade*	Diversity_CBG_Edu_Graduate*	Diversity_CBG_Owner_Occupied*	Diversity_CBG_PercentLowWage	Diversity_CBG_Pop_Mean_Income*	Diversity_CBG_TripEquilibrium	Diversity_Emp_Entropy_8	Diversity_Emp_Equilibrium	Diversity_Emp_JobsPerHousehold*	Diversity_Emp_WorkersPerJob*	Diversity_Region_Emp_Diversity	Diversity_Region_Emp_WkrsPerJob
National	412	198	36.59	161	294	0.24	831	0.44	0.61	0.36	4.86	7.51	0.28	0.46
Atlanta	458	239	35.40	169	341	0.25	957	0.46	0.63	0.39	2.31	6.47	0.31	0.49
Austin	551	240	38.89	210	321	0.23	1,018	0.47	0.64	0.43	2.74	5.05	0.33	0.51
Baltimore	354	167	42.59	181	302	0.22	773	0.40	0.55	0.31	3.25	9.44	0.26	0.42
Boston	373	130	42.00	206	291	0.28	740	0.48	0.71	0.41	6.63	0.56	0.11	0.16
Charlotte	427	205	23.06	127	347	0.25	835	0.47	0.65	0.44	5.97	4.37	0.34	0.52
Chicago	416	163	53.35	193	315	0.22	806	0.39	0.55	0.31	2.49	10.52	0.25	0.45
Cincinnati/Dayt	322	171	21.01	116	327	0.27	738	0.45	0.61	0.39	2.09	7.69	0.28	0.50
Cleveland	312	179	31.27	114	329	0.27	780	0.47	0.63	0.39	3.24	6.08	0.31	0.51
Columbus	438	217	30.26	144	355	0.25	898	0.45	0.63	0.40	2.36	7.69	0.31	0.51
Dallas/Ft Worth	348	200	22.66	119	210	0.23	781	0.38	0.55	0.32	4.40	11.51	0.27	0.41
Denver	439	192	34.04	166	290	0.23	843	0.43	0.60	0.36	2.67	6.49	0.34	0.43
Detroit	270	176	19.74	109	265	0.28	687	0.42	0.56	0.35	2.07	8.90	0.25	0.47
East	450	204	27.89	183	261	0.21	783	0.43	0.63	0.32	1.86	5.49	0.27	0.45
Hampton Roads	309	228	18.22	108	273	0.29	750	0.42	0.63	0.35	2.96	8.45	0.26	0.47
Hartford	284	132	24.70	127	263	0.22	687	0.46	0.62	0.42	3.27	5.90	0.25	0.36
Houston	514	288	40.09	193	420	0.23	1,064	0.43	0.62	0.38	2.76	7.48	0.29	0.49
Indianapolis	448	224	36.36	145	422	0.26	945	0.42	0.60	0.40	2.73	8.69	0.31	0.49
Inland Empire	300	266	16.58	82	285	0.26	834	0.46	0.62	0.34	1.47	6.60	0.18	0.47
Kansas City	343	177	28.42	127	287	0.27	738	0.45	0.63	0.40	3.28	6.00	0.32	0.51
Las Vegas	261	227	15.05	56	199	0.23	723	0.39	0.55	0.32	3.65	13.61	0.21	0.43
Long Island	363	126	37.94	155	177	0.22	660	0.32	0.52	0.24	6.49	14.60	0.18	0.39
Los Angeles	480	230	41.27	147	208	0.28	881	0.49	0.64	0.34	5.08	4.49	0.26	0.49
Milwaukee/Mad	417	160	38.83	160	332	0.27	803	0.43	0.58	0.36	3.23	7.04	0.31	0.48
Minneapolis/St	430	175	32.67	133	329	0.25	794	0.49	0.63	0.42	3.00	4.96	0.38	0.52
Nashville	474	247	28.66	152	426	0.26	971	0.41	0.61	0.38	3.07	9.36	0.30	0.47
New York City	561	100	117.05	337	186	0.17	885	0.46	0.65	0.37	3.85	4.52	0.29	0.48
Northern New	385	143	32.99	190	261	0.22	712	0.45	0.59	0.37	2.77	7.73	0.30	0.49

Orange County	463	229	33.55	141	233	0.22	783	0.43	0.61	0.31	5.88	8.64	0.24	0.43
Orlando	939	466	50.53	244	674	0.28	1,694	0.46	0.68	0.37	2.05	4.05	0.29	0.51
Philadelphia	334	147	33.41	141	334	0.24	727	0.44	0.62	0.38	4.00	6.92	0.29	0.50
Phoenix	281	186	16.30	87	210	0.24	689	0.39	0.55	0.32	2.37	13.03	0.25	0.42
Pittsburgh	332	111	33.34	145	323	0.25	676	0.47	0.63	0.41	10.64	4.67	0.35	0.51
Portland	426	234	31.66	150	339	0.24	866	0.51	0.70	0.43	2.14	3.18	0.32	0.54
Raleigh/Durham	619	213	46.57	283	426	0.23	1,069	0.46	0.65	0.39	3.39	7.30	0.37	0.48
Sacramento	332	230	25.55	96	269	0.25	735	0.48	0.64	0.37	1.58	5.69	0.23	0.50
Salt Lake City	396	262	19.91	104	332	0.30	822	0.48	0.71	0.46	6.27	2.17	0.41	0.52
San Antonio	398	251	30.96	124	304	0.27	875	0.46	0.62	0.40	2.31	5.56	0.30	0.50
San Diego	510	274	42.73	176	339	0.24	916	0.45	0.61	0.33	1.75	9.14	0.22	0.47
San Francisco	608	216	85.58	283	256	0.20	1,007	0.51	0.67	0.39	27.13	3.17	0.35	0.48
Seattle/Puget	441	189	31.72	174	239	0.20	833	0.45	0.64	0.38	2.85	4.44	0.34	0.48
South Bay/San	552	186	38.85	369	296	0.18	902	0.46	0.67	0.34	61.46	4.41	0.27	0.49
South Florida	396	191	34.98	111	291	0.25	774	0.41	0.56	0.33	27.16	12.13	0.24	0.45
St. Louis	368	194	35.38	148	368	0.28	778	0.47	0.65	0.41	2.31	4.27	0.33	0.51
Tampa/St	363	196	23.98	110	311	0.26	795	0.44	0.60	0.38	1.92	5.39	0.25	0.49
Washington, DC	403	155	70.24	270	266	0.18	825	0.41	0.56	0.33	2.89	10.04	0.30	0.43
West Michigan	301	177	17.90	109	309	0.28	721	0.46	0.59	0.42	2.24	6.20	0.30	0.53
Westchester/So Connecticut	229	124	22.70	101	133	0.24	579	0.33	0.47	0.26	1.62	13.93	0.20	0.40