The Need for Speed:
Internet Infrastructure Location and Real Asset Values

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ABSTRACT

Fast data access and flows are crucial to the competitive success of many firms as they navigate the real effects of latency in the digital economy. Using an extensive, hand-collected dataset of U.S. internet exchange points (IXPs), office property transaction data, and tenant lease information, we examine real asset pricing and tenant agglomeration effects arising from the geographic location of internet infrastructure. Estimating hedonic and spatial regression models, we document significant price premiums for office property transactions located within one-half mile of an IXP. A one standard deviation decrease in linear distance from an IXP is associated with a 13 percent decrease in sale price. Using difference-in-difference analysis and numerous spatial characteristics, we also provide a battery of robustness checks to confirm and sharply identify our findings. As an important demand-driven channel for our findings, we document a significant increase in demand for office space surrounding IXPs by tenants in knowledge and technology intensive (KTI) industries following IXP establishment. This collocation effect is associated with higher effective rents in properties surrounding IXPs and the magnitude of the effect is greater among KTI tenants.

JEL Classification: D23, D24, O18, O33

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1. Introduction

The prevalence of the information economy is reshaping how investors and policy makers think of essential community infrastructure. Just as traditional infrastructure (e.g., water, electricity, and transportation systems) was designed to encourage the movement of key assets and individuals within a local community, the geographic placement of technology infrastructure is intended to facilitate the efficient exchange of a new critical asset, data. As the geographic footprint of the internet's physical infrastructure has continued to expand, fast data access and flows have become increasingly crucial to many firms -- with latency being the proverbial "Achilles heel" to competing effectively. Firms must now weigh the business tradeoffs of potential lost revenues against increased technology infrastructure costs as they navigate the real effects of latency in the digital environment (Minnear, 2011).[1]

To minimize the impact of latency, it is often imperative for firms to strategically locate their facilities near internet infrastructure and access points as the physical distance between internet users still plays a key role in determining latency effects.[2] This too can be costly to the firm as property rental or ownership expenses increase due to heightened demand for physical space in close geographic proximity to the physical infrastructure of the internet. For some firms, such as those operating in knowledge and technology intensive (KTI) industries, the competitive advantage associated with geographic proximity to technological infrastructure may outweigh the associated costs due to their need for internet speed. The increased demand for scarce physical space can have real economic effects on the local community as tenants that are most likely to benefit from, and thereby willing to pay for, proximity to internet infrastructure access points competitively bid on available space. The competitive allocation of leasable space to technology intensive tenants can lead to significant shifts in tenant composition and real asset values in the areas surrounding the

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[1] The chief cloud architect for Netflix, Adrian Cockcroft, states the following when describing the tension firms now manage between latency penalties and increased technology costs in navigating the digital economy (Babcock, 2013), "Mastering these business tradeoffs of weighing the cost and latency penalties, when they exist, against your business goals is one of the fundamental challenges of cloud computing." Cockcroft used a rough equation to formulate the trade-off: "How many dollars should you spend to reduce customer latencies by 50% if that increases your conversion rate by 10%?"

[2] Many financial firms have invested substantial capital into moving the physical infrastructure of their computer networks to be in close geographic proximity to the data centers of the stock exchange and news outlets for precisely this reason (Stibel, 2013).

technology infrastructure, thus providing a local benefit that may not otherwise be fully represented in the documented weak risk-adjusted performance of infrastructure investment funds (e.g. Andonov, Kraussl, and Rauh, 2021; Gupta and Van Nieuwerburgh, 2021).[3]

In this paper, we examine tenant agglomeration (i.e., clustering) and real asset value effects of the location of internet infrastructure. Specifically, we utilize a novel dataset of internet exchange point (IXP) locations and commercial real estate (CRE) transaction data to document a collocation premium in office sale prices and rents surrounding an IXP.[4] We attribute these premiums to tenant-based demand from firms operating in KTI industries that cluster their operations in properties within close proximity to an IXP. We are the first to document real asset pricing effects and tenant agglomeration associated with the establishment and location of internet infrastructure

Our empirical analysis begins by examining the relation between physical distance to the nearest IXP and CRE values using data that includes approximately $30 billion of office property transaction value over a 21-year period (1999-2019) in 25 major U.S. metropolitan markets. Estimating both standard hedonic and spatial regression models of transaction prices on distance to an IXP, we document a significant price premium among office properties located closest to an IXP. A one standard deviation increase in linear distance to an IXP is associated with a 13 percent decrease in sale price. Importantly, the economic magnitude of the price premium nearly doubles for properties located within ½ mile of an IXP, relative to those located outside of this threshold; however, the price effect is insignificant at distances greater than 1½ miles from an IXP.

To further sharpen our identification of the IXP effect, we also conduct a multivariate difference-in-difference analysis centered on the year in which an IXP was established. Combining the granularity of IXP location data with the precise timing of IXP establishment aids in our identification of agglomeration and valuation effects associated with this technological innovation. We identify a significant increase in property valuations around the establishment of an IXP for properties located within ½ mile of this internet access point.[5]

[3] An extensive literature examines the effects of "traditional" public infrastructure on local economic productivity and real asset values (e.g., Aschauer, 1989; Roller and Waverman, 2001; Cadot, Roller, and Stephan, 2006; Donaldson, 2018; Gupta et al., 2021; Gupta, Kontokosta, and Van Nieuwerburgh, 2022).

[4] Anecdotal evidence consistent with our findings is a real estate transaction that occurred near an interconnect hub in downtown Los Angeles. One Wilshire, an office building, sold for a record $437.5 million because it is one of the three leading telecommunications interconnect hubs in the world (Vincent, 2013). This transaction illustrates the valuation effects of reducing latency by colocation.

[5] As an alternative to the difference-in-difference approach, we also estimate Heckman (1979) two-stage regressions that utilize local demographic information on technology use. This additional test helps further

These additional tests provide further causal evidence that proximity to an IXP location is associated with higher valuations after the IXP has been established at its current location, thereby mitigating concerns that our primary specifications are capturing price effects unrelated to the establishment of the IXP.

We next examine a tenant-based demand channel to explain the pricing premium we document. This investigation requires more granular data than available in our transaction price data. We therefore incorporate data on individual lease transactions within single and multi-tenant office buildings, including information on rental rates, lease characteristics, and the building's tenant composition. The tenant-based channel has two primary implications for our valuation analysis: (1) we should observe higher effective rents in properties surrounding an IXP due to the demand-driven effects of tenant agglomeration, and (2) the impact of IXP distance on observed rents should be greater for tenants working in KTI industries as these tenants are likely to benefit most from, and thereby willing to pay for, proximity to an IXP. Consistent with our transaction price results, we find that distance to an IXP has a significant effect on rents paid.[6] We also find an economically significant increase in KTI tenants following the establishment of an IXP--the relative KTI increase is 17%. These additional results highlight the importance of a demand-driven channel stemming from KTI tenants' desire for leasable space closest to an IXP. Our documented industry agglomeration findings around IXP locations help clarify the channel through which distance to an IXP impacts rental rates and further identify the capitalization of rents as an important explanation for the documented IXP distance pricing effects. Taken together, our transaction price, rent, and tenant composition results underscore the important interplay between technological innovation, real asset location, agglomeration, and valuation effects.

Our empirical specifications are robust to the inclusion of observable building characteristics, locational attributes, property type classifications, time trends, and a spatial component designed to capture potential dependence among neighboring property transactions, as well as potential omitted locational and structural characteristics correlated with distance to the IXP. Our results are also robust to controlling for numerous other spatial linkages such as distance to the MSA's central business district, distance to the geographic

mitigate potential sample selection bias concerns related to both observable and unobservable factors associated with differences in property transactions before and after the establishment of an IXP.

[6] These rent results contribute to a growing literature examining asset-level risk factors that impact rental income and total returns in real estate markets (e.g., Eichholtz et al., 2021; Chambers, Spaenjers, and Steiner, 2021; Sagi, 2021).

center point of the MSA, and distance to the closest major airport, as well as other MSA characteristics such as population density, the concentration of IXPs, and "gateway" city designations that may otherwise be associated with heightened demand, land supply constraints, and higher property valuations. We also find that our IXP distance effect remains statistically and economically significant in a subsample of property transactions occurring in MSAs without heavy or light rail metropolitan commuting systems. These additional robustness tests further isolate our technology infrastructure pricing effect from property linkages to other traditional forms of community infrastructure that may exist within an MSA.

Our paper makes three key contributions to the literature. First, we contribute to the literature on the real effects of infrastructure investments (e.g., Aschauer, 1989; Roller and Waverman, 2001; Cadot, Roller, and Stephan, 2006; Donaldson, 2018; Goetzmann, Spaenjers, and Van Nieuwerburgh, 2021; Gupta et al. 2021) by documenting significant real asset value and industry agglomeration effects from information-based internet infrastructure investments. While several recent studies on infrastructure investment further document low risk-adjusted performance for investors in closed-end (Andonov, Kraussl, and Rauh, 2021) and private equity funds (Gupta and Van Nieuwerburgh, 2021), our study highlights the positive CRE valuation effects from internet infrastructure investments. Our research also contributes to recent research showing land and housing price capitalization effects of more traditional infrastructure, such as new urban rail (e.g., Gibbons and Machin, 2005; Bowes and Ihlandfelt, 2001; Kahn, 2007; Gupta, Kontokosta, and Van Nieuwerburgh 2022).[7] Contributing to this literature stream, we are the first to document the CRE valuation and tenant agglomeration effects associated with the location of new internet infrastructure.

Second, we contribute to the recent literature on the importance of latency effects in financial markets by documenting a significant shift in the demand for physical space surrounding an IXP by KTI tenants around the time of the IXP's establishment. Competition based on relative speed is an important characteristic of markets in which trading firms invest aggressively in both location and technology to gain a speed advantage over their

[7] The rail-based infrastructure literature finds price premiums in the 3-10 percent range, with Gupta, Kotokosta, and Van Nieuwerburgh, 2022 finding 8% price premiums.

rivals.[8] Recent research suggests that relative speed can have significant effects on liquidity and the gains from trade amongst financial market participants (e.g., Brogaard et al., 2015; Menkveld and Zoican, 2017, and Shkilko and Sokolov, 2020). Cheng, Li, and Naranjo (2016) further suggest that latency concerns extend more broadly to a firm's cloud computing operational decisions and that a firm's optimal cloud computing location selection should factor into pricing-latency effects, both in terms of cloud bidding location as well as firm operational location choices. Our study extends this line of research by documenting a significant shift in the concentration of KTI tenants around the geographic placement of an IXP and their willingness to pay a premium for collocation benefits.[9]

Finally, we contribute to the expansive agglomeration literature, with a focus on the causes of agglomeration and the real and financial effects associated with agglomeration. This literature provides compelling evidence that local economic activity is spatially concentrated, with productivity, employment, wages, and rent often used to measure agglomeration economies (Rosenthal and Strange, 2020). Our analysis provides evidence on the micro foundational forces that generate agglomeration economies (Rosenthal and Strange, 2001). We show that proximity to internet infrastructure has a significant impact on KTI agglomeration and that this agglomeration attenuates rapidly due to latency effects associated with distance.[10] Importantly, we further show that agglomeration effects arising from internet infrastructure proximity also have significant financial effects – resulting in higher demand driven rents and pricing premiums. This result contributes to the findings of Liu, Rosenthal, and Strange (2018) who find that rents are positively related to the intensity of activity within a building's zip code. While their findings center on industries that use office space, such as law, finance, and business services (industries that have come to dominate downtowns), our findings focus on KTI industries located near important internet infrastructure. Taken together, our results suggest that while the information technology

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[8] Similarly, in pursuing the need for speed, "high-frequency traders are using an experimental type of cable to speed up their systems by billionths of a second, the latest move in a technological arms race to execute stock trades as quickly as possible" (Osipovich, 2020).

[9] Our focus on the importance of geographic proximity to information technology infrastructure also complements recent work examining the real effects of information dissemination technologies on financial markets (e.g., Goldstein, Yang, and Zuo, 2022).

[10] Examining agglomeration attenuation effects in other sectors, Rosenthal and Strange (2003) conclude that spillover effects shrink by roughly half after five miles, while Rosenthal and Strange (2005) find effects that are notably smaller after one mile. Arzaghi and Henderson (2008) report evidence that among advertisers, spillovers attenuate a little less than half a mile. Ahlfeldt et al. (2015) similarly suggest rapid attenuation measured on travel time, not distance.

revolution results in less agglomeration in some areas and sectors due to improved connectivity, it increases agglomeration in other areas and sectors due to the importance of proximity to internet infrastructure.

2. Internet Exchange Points (IXPs)

While at times it may seem as if the internet is all around us, the transfer of information between users is facilitated by a complex, interconnected system of physical computing devices (e.g., routers, switches, cables, etc.) that are geographically dispersed throughout the world. In the U.S., information travels across a vast network of broadband and fiber-optic cables whose pathways closely resemble those of the national transportation infrastructure. To illustrate, we reproduce a map of the U.S. long-haul fiber optic network, previously constructed by Durairajan, Barford, Sommers and Willinger (2015), in Panel A of Figure 1. Internet service providers (ISPs), such as Verizon or Comcast, provide the initial user with the medium for transferring information. However, information can then follow a multiplicity of paths along the internet's infrastructure enroute to its end user. When multiple service providers are involved, the efficient transfer of information along these pathways relies on the existence of internet exchanges maintained by independent commercial organizations or member associations. The physical location where two or more ISPs meet to exchange data is referred to as an internet exchange point (IXP). Panel B of Figure 1 plots the geographic location of our hand-collected sample of 374 IXPs dispersed throughout the U.S.[11] While clusters of IXPs are observed in major metropolitan markets, there are also a significant number of IXPs located in suburban or rural locations.

Geographic proximity to an IXP can provide numerous benefits to businesses, particularly those in KTI industries. Not only does proximity to an IXP serve to shorten the path that data must travel between users, thereby impacting the speed of information transmission, but it also can reduce tangible infrastructure costs that businesses face in establishing or increasing the quality of network connectivity.[12] Furthermore, closeness to an

[11] We collect our dataset of U.S. IXPs using information obtained from three primary sources: *Peering DB, Telegeography*, and *Packet Clearing House*. Further details are provided in *Data and Summary Statistics*.

[12] In one of the earliest studies on the response time effect on user behavior, Miller (1968) showed that ten seconds is the threshold for user attention. However, in today's environment consumers become impatient when web pages take longer than two seconds to load (Forrester Consulting, 2009). These user attention thresholds are important because a subpar Web experience results in lost revenue and unfavorable customer perceptions. For example, an increase of 100ms response time can result in a 1% drop of sales at Amazon (Mazzucco, 2010), and Google's traffic will drop by 20% for half a second increase in returning search results (Mayer, 2009).

IXP can also have security implications as it limits the number of interception points at which sensitive data could be compromised.

To the extent these competitive advantages impact operational location choice for firms in KTI industries, we expect to observe a clustering of KTI tenants in properties surrounding an IXP. However, because a firm's competitive advantage fades with distance to the IXP, we expect lower proportions of KTI tenants to be present in more distant properties. When coupled with the inherent scarcity of leasable space surrounding an IXP's location, the increased demand in the area immediately surrounding IXP location can also serve to increase rents, and by extension property values, as tenants competitively bid on scarce available space. However, over longer distances to the IXP, we expect the asset valuation effects of tenant agglomeration to dissipate.

To motivate this demand-driven channel of tenant agglomeration and asset valuation effects around an IXP, Figure 2 displays a series of illustrative heat maps depicting the relative concentration of value, in terms of transaction price (Panel A), effective rent (Panel B), and tenant composition (Panel C) in office buildings surrounding a cluster of IXPs in Miami, Florida.[13] Panel A clearly depicts a strong univariate relation between geographic proximity to an IXP and transaction values, with greater valuations concentrated in properties surrounding the IXP. As distance to the IXP increases, however, property values appear to decline. In Panel B, we observe a similar relation when examining effective rents on leased space located within properties in close proximity to an IXP. Furthermore, tenants from KTI industries appear to cluster their operational locations around IXPs (Panel C). Thus, Panels B and C provide an initial indication that the observed asset value effect appears to align with increased demand from KTI tenants resulting in higher rents for leased space concentrated around an IXP. Taken together, this figure provides some motivational univariate relations that are consistent with agglomeration-based value effects associated with the establishment of an IXP. Our subsequent empirical analyses are designed to carefully test and document the observed price-distance gradient surrounding internet infrastructure and demand-driven channel through which this pricing effect occurs.

[13] Transaction price data is obtained from CoStar, while effective rent and tenant composition information is provided by CompStak. Further details are provided in *Data and Summary Statistics*.

3. Empirical Methodology

We first estimate both standard hedonic and spatial regression models to empirically test the relation between geographic proximity to an IXP and commercial property transaction prices. The standard hedonic framework relates the property's transaction price to observable building characteristics, locational attributes, property type classifications, and time trends in a linear regression framework. Spatial models extend the hedonic framework by including a spatial component in the regression estimation that is designed to capture potential dependence among neighboring property transactions, as well as omitted locational and structural characteristics correlated with distance to the IXP.

3.1 Hedonic Regression Model

Our baseline semi-log hedonic regression model has the following form (e.g., Rosen, 1974):

$$\begin{aligned} LN\_PRICE_i = \phi &+ \lambda_1 IXP\_DIST + \lambda_2 AGE + \lambda_3 AGE^2 + \lambda_4 BLDG\_SQFT + \lambda_5 BLDG\_SQFT^2 \\ &+ \lambda_6 LAND\_SQFT + \lambda_7 LAND\_SQFT^2 + \lambda_8 FLOORS + \lambda_9 LONG + \lambda_{10} LAT \\ &+ \lambda_t T + \lambda_r R + \lambda_s S + \varepsilon_m \end{aligned} \tag{1}$$

where:

LN_PRICE =	The natural logarithm of the sale price;
Φ=	A constant term;
IXP_DIST=	Distance in miles between the property transaction and the location of the nearest IXP;
AGE =	Age of the structure(s) in years;
AGE^2=	The square of AGE;
$BLDG\_SQFT$=	Total square footage of structure(s) in thousands;
$BLDG\_SQFT^2$=	The square of $BLDG\_SQFT$;
$LAND\_SQFT$ =	Land square footage in thousands;
$LAND\_SQFT^2$=	The square of $LAND\_SQFT$;
$FLOORS$=	Number of floors in property;
$LONG$=	Longitude coordinate of the property;
LAT=	Latitude coordinate of the property;
T=	A vector of year dummies denoted by year t;
R=	A vector of geographic submarket dummies denoted by submarket r;
S=	A vector of sub-property type dummies denoted by sub-property type s;
ε_m=	An error term.

Our primary test variable is linear distance in miles between the property transaction and the location of the nearest IXP. Distance is calculated based on the longitude and latitude coordinates of the transacted property and the building that houses the IXP. We expect transaction prices to be negatively related to distance to the nearest IXP.

We further expect transaction prices to be negatively related to the age of the property and positively related to the square footage of the land and improvements. We also include indicator variables describing the overall quality of the property: Class A, Class B, or other (lower) class designation. Indicator variables to denote the property's condition and the primary construction material are also included.[14] An advantage of including class, building condition, and building material variables is that they are likely correlated with other unobserved indicators of the property's quality. We also include longitude and latitude as explanatory variables to control for property specific locational attributes.

To further control for any bias that may result from omitted locational and structural characteristics that are correlated with our main variables of interest, we include year fixed effects as well as fixed effects for both the sub-property type of the office structure and the CoStar defined geographic submarket in which the property is located.[15]

3.2 Spatial Regression Model

Although hedonic models can be designed to carefully control for observable property characteristics and the inclusion of neighborhood fixed effects can control for absolute price differences across geographic segments, the transaction prices of properties within a close geographic proximity of one another may be correlated if they incorporate exposures to a common set of unobservable or omitted determinants of value that are linked at the local level. Thus, omitting spatial dependence from property-level pricing analysis may lead to spurious inferences when interpreting the impact of other factors in a traditional hedonic

[14] CoStar's property condition classifications include the following: adequate, excellent, good, needs improvement, and poor; CoStar's construction material classifications include the following: masonry, metal, reinforced concrete, steel, and wood. In each case, an additional category takes on a value of one if the property's condition or construction material is missing.

[15] CoStar's office subtypes include the following mixed-use classifications: Office (Community Center), Office (Lifestyle Center), Office (Neighborhood Center), Office (Outlet Center), Office (Power Center), Office (Regional Mall), Office (Strip Center), Office (Super Regional Mall), Office (Theme / Festival Center). These subtypes constitute less than 1 percent of our sample of office transactions. CoStar defines geographic submarkets based on discussions with local brokers. There are 787 distinct CoStar delineated geographic submarkets across our 25 MSAs, or an average of 31 submarkets per MSA. The number of geographic submarkets in gateway MSAs (i.e., New York, Boston, San Francisco, Chicago, Los Angeles, and Washington DC) is even larger with an average of 51 submarkets across these six MSAs. CoStar's submarket delineations are preferable to the use of zip codes and census-tract groups, neither of which are constructed specifically to capture the dynamics of office property submarkets as defined by market participants.

framework. Spatial regressions help mitigate this concern by allowing for spillover effects based on relative geographic proximity to be incorporated into the model of the price formation process.

Consistent with prior research highlighting the importance of controlling for a spatial parameter in an analysis of property transaction prices (e.g., Pace et al., 2000), we extend our basic hedonic regression framework by estimating a spatial autoregressive (SARAR) model (Kelejian and Prucha, 2010) of the following form:

$$P = \rho W P + X\beta + T\delta + R\theta + S\gamma + \varepsilon, \tag{2}$$

$$\varepsilon = \lambda W \varepsilon + \mu. \tag{3}$$

P is a n x 1 vector of log transaction prices where n denotes the number of property observations in our dataset; X is a n x k matrix of property characteristics in which k denotes the number of observable property characteristics as specified in our basic hedonic regression; T is a n x t matrix of year dummies where t denotes the sample year; R is a n x r matrix of submarket dummies where r denotes the CoStar defined geographic submarket classification; S is a n x s matrix of s property subtype dummies; and W is a n x n weight matrix that measures the geographic distance between each individual property observation and the remaining transactions in our database. Each row in the weight matrix, W, corresponds to an individual transaction and each weight is assigned based on the inverse distance in miles between the subject property and each property in the dataset. Distance is measured using the latitude and longitude coordinates of each property transaction. We also utilize the weight matrix to control for possible spatial autocorrelation in the error term (Kelejian and Prucha, 2010).

4. Data and Summary Statistics

We collect an extensive dataset of U.S. IXPs using information obtained from three primary sources: *Peering DB, Telegeography*, and *Packet Clearing House*.[16] In particular, we collect the following information: internet exchange name, property name, street address, city, state, zip code, latitude, longitude, and year established. We identify 374 unique IXPs that are geographically dispersed throughout the United States. Deleting IXP locations for

[16] https://www.peeringdb.com/; https://www2.telegeography.com/; https://www.pch.net/

which the year of establishment could not be determined reduces our IXP sample to 311 locations.

Panel A of Figure 3 displays the time series distribution of IXP establishments. During our sample period (1999-2019), we observe the establishment of 290 new IXPs. While there is time variation in their creation, approximately half were established from 2012 to 2016. In Panel B of Figure 3, we focus on the IXPs located within the geographic boundaries of our 25 MSAs. Nearly 60 percent (177 unique IXPs) of observable IXPs were established within the boundary of these 25 MSAs. On average, there are approximately 7 IXPs located within an individual MSA in our sample. The MSAs with the highest concentration of IXPs are New York, Washington, D.C., Miami, Chicago, and Dallas; the MSAs with the fewest are Minneapolis, Richmond, Sacramento, San Antonio, and Philadelphia. In some MSAs, the closest IXP to a property transaction is located outside of the MSA boundary. Thus, we retain all IXPs with an available establishment year in our dataset to ensure that we capture the minimum distance to an IXP for all property transactions occurring within a MSA.

4.1 Transaction Data

We obtain office property transaction data from CoStar, a leading provider of comprehensive CRE data, for the period spanning January 1999 through December 2019. Our 25 U.S. metropolitan markets were chosen based on (1) whether the MSA was ranked as one of the top 30 most populous MSAs in at least two of the last three United States Census reports (i.e., 1990, 2000, 2010) and (2) included at least one IXP within its geographic boundary. Our final sample includes property transactions from the following MSAs: Atlanta, Boston, Chicago, Dallas/ Ft Worth, Denver, Detroit, Houston, Indianapolis, Kansas City, Los Angeles, Miami, Minneapolis, New York City, Philadelphia, Phoenix, Pittsburgh, Portland, Richmond, Sacramento, San Antonio, San Francisco, Seattle, Saint Louis, Tampa/St. Petersburg, and Washington DC. In addition, we restrict our analysis to office properties with a recorded sale price of at least $500,000.

The original dataset contains 104,393 CoStar verified sale transactions. We eliminate transaction records missing one or more of the variables required for our hedonic regressions. This reduces our usable sample to 97,504 observations. We also exclude sale transactions associated with a "special condition," including sales that are part of an auction, sales that involve the use of Section 1031 tax-deferred exchanges, sale-leaseback transactions, bulk portfolio sales, bankruptcy sales, and properties classified as "high vacancy" properties by CoStar. The elimination of these non-arms-length and other "atypical" transactions further reduces our sample to 52,078 observations. Removing transactions that occurred before the first IXP was established within a MSA reduces our final regression sample to 30,368 observations.

Table 1 presents summary statistics for our final office property sample. The mean (median) distance between sample properties and the nearest IXP is 8.4 (6.4) miles. Approximately 5 percent of sale transactions are located within one-half mile of the IXP (*IXP < ½ Mile*), 6 percent are located between one-half mile and one mile (*IXP ½ Mile to 1 Mile*), 5 percent are between a mile and one and one-half mile (*IXP 1 Mile to 1 ½ Mile*), and 4 percent are between one and one-half mile and two miles (*IXP 1 ½ Mile to 2 Miles*). Slightly more than 80 percent of sale transactions are more than two miles from the nearest IXP.

The mean transaction price is $12.7 million; however, the median price of $1.7 million reveals a sale price distribution that is highly skewed to the right. The average property is 47 years old, contains 51 thousand square feet of constructed space, and is built on a 101 thousand square foot land parcel. The average (median) property contains 3.3 (2.0) floors. Only 11.3 percent of the office transactions involved "Class A" properties as designated by CoStar; 47.0 percent of the sample properties are classified as "Class B" properties.[17] Clearly, our CoStar database is more representative of the universe of office properties than a sample based exclusively on "institutional quality" properties.[18] The dominant property condition is "adequate," and the most frequent construction type is masonry.

5. IXP Distance and Property Value

Column 1 of Table 2 contains the results from estimating our baseline hedonic price regression.[19] P-values are reported in parentheses; *, **, and *** denote statistical

[17] Class A typically refers to newer structures located in major metropolitan areas that have market values in excess of $10 million and are the most prestigious in tenancy, location, amenities, and desirability. Class B refers to buildings that have a less desirable location, fewer amenities, or a relatively inefficient layout of leasable space. Class C denotes properties that may have once been Class A or Class B that are now older and reasonably maintained but are below current market standards for one or more reasons.

[18] Results that exclude properties with transaction prices less than $5 million are very similar. In fact, the absolute magnitude of the IXP pricing effect is approximately 1.6 times greater when we focus our analysis on this subsample.

[19] With this semi-log functional form, the percentage price effect with a unit change in a property characteristic is obtained by (exp(coefficient)-1)*100.

significance at the 10, 5, and 1 percent level, respectively. This model explains 74 percent of the variation in sale prices. The estimated coefficient on *IXP_DIST* is negative and highly statistically significant. A one standard deviation increase in *IXP_DIST* is associated with a 12.7 percent decrease in sale price, representing an economically significant effect. This result is consistent with our hypothesis that distance to an IXP is an important determinant of value.

As expected, the estimated coefficient on property *AGE* is negative and highly significant; however, the estimated coefficient on AGE^2 is positive and highly significant. This quadratic relation between price and age suggests a positive "vintage" effect for older properties. The estimated coefficient on *BLDG_SQFT* is positive and highly significant, as expected, whereas the estimated coefficient on $BLDG\_SQFT^2$ is negative and highly significant. These results strongly suggest the relation between sale price and building size is also nonlinear. The estimated coefficients on *LAND_SQFT* and $LAND\_SQFT^2$ follow a similar pattern. When controlling for land and building square footage, the estimated coefficient on *FLOORS* is negative and significant.[20]

Column 2 of Table 2 reports results from estimating our baseline spatial regression. The estimated coefficient on *IXP_DIST* is again negative and highly significant. The estimated coefficients on our other control variables are largely indistinguishable from the coefficient estimates in the hedonic regression. However, the estimated coefficients on both the spatial dependence term and the spatial error term are positive and highly significant. This suggests that, in our office sample, the transaction prices of properties near each other incorporate exposures to a common set of value determinants not included in our hedonic regression specification. We therefore report results from the estimation of spatial regression models in the remainder of our transaction price analysis.

5.1 Robustness Tests: Controlling for MSA Characteristics and Other Distance Measures

Although our main specifications include submarket fixed effects to capture local determinants of value, it is possible that distance to the nearest IXP is correlated with characteristics of the MSA in which the transacted property is located. Panel A of Table 3

[20] The number of floors in an office building is highly correlated with both property quality classifications (Class A indicator (ρ=0.47)) and property size (*BLDG_SQFT* (ρ=0.81)).

presents coefficient estimates from spatial regressions of price on distance to an IXP, controlling for the following MSA characteristics: population density, number of IXPs, and gateway classification. If metropolitan areas with greater population density tend to have higher property valuations due to heightened demand for office space or land supply constraints, it is possible that the IXP effect we document could be driven by this omitted MSA-level characteristic. We therefore construct an indicator variable, *HI_POPDENS,* which denotes a MSA with a population density above the median value of our sample MSAs.[21]

Similarly, the concentration of IXPs within a particular MSA may be indicative of omitted demand side factors that influence transaction prices. Thus, we construct *HI_IXPCOUNT*, an indicator variable set equal to one if the total number of IXPs is above the median among our sample MSAs. Finally, we consider pricing differentials in "gateway" cities as a potential driver of our IXP effect. Consistent with industry practice, we define *GATEWAY* as an indicator variable denoting a MSA that is commonly referred to as a "gateway" city: New York, Boston, San Francisco, Chicago, Los Angeles, and Washington DC.[22] These MSAs are thought to have investment advantages over the remaining 360-plus MSAs, including increased liquidity and information revelation due to the size and depth of these markets and the amount of market research directed at them (Ling et al., 2019; Pagliari, 2021). If these cities contain a disproportionate number of IXPs, and property valuations in these cities are typically higher, it is possible that our documented IXP effect is driven by fundamental factors common among these premium markets. Each of these indicator variables is also interacted with *IXP_DIST* to more precisely determine if inclusion of the MSA characteristic affects the estimated coefficient on *IXP_DIST*.

The results reported in the first column of Panel A include *HI_POPDENS* as an additional regressor. The estimated coefficient on *HI_POPDENS* is positive and highly significant, indicating higher transaction prices in higher density MSAs, all else equal. However, the inclusion of *HI_POPDENS* only marginally reduces the magnitude of the coefficient on *IXP_DIST*, which remains significant at the 1 percent level; moreover, the estimated coefficient on *HI_POPDENS** IXP_DIST* cannot be distinguished from zero.

[21] Fisher et al. (2020) find that location density is an important determinant of REIT performance outcomes and financing choices, consistent with geographical characteristics playing a significant role in driving patterns of investment risk and return across commercial real estate markets.
[22] See, for example, Pai and Geltner (2007) and Geltner et.al. (2014).

Similarly, we find that transaction prices are positively and significantly related to the number of IXPs in the MSA (*HI_IXPCOUNT*=1) and whether the MSA is a gateway market (*GATEWAY*=1). Nevertheless, the inclusion of these MSA characteristics only slightly reduces the magnitude of the coefficients on *IXP_DIST*, which remain significant at the 1 percent level in all specifications. Importantly, the coefficient estimates on *IXP_DIST* are not statistically different in these MSAs, as evidenced by the insignificant coefficients on the interaction terms. Overall, these results strongly suggest that the estimated negative relation between distance to the nearest IXP and transaction prices we document is not driven by omitted MSA characteristics that are correlated with distance to the nearest IXP.[23]

The inclusion of a spatial parameter in our regression framework likely captures omitted locational attributes. However, for robustness we construct the following three additional distance measures to capture the potential impact of property linkages to other community infrastructure located throughout a MSA: *CBD_DIST* is the distance in miles between the transacted property and the center point of the MSA's central business district (CBD); *MSA_DIST* is distance to the geographic center point of the MSA; and *LINKAGE_DIST* is distance to the closest major airport.[24] If proximity to these alternative locations within a MSA results in higher property valuations, we would expect to observe a negative relation between their distance from the transacting property and the property's sale price. Furthermore, if distances to these other locations are correlated with *IXP_DIST*, the estimated coefficient on *IXP_DIST* may be capturing a portion of their omitted effect.

We separately include these alternative distance measures and re-estimate our spatial regression models. The results reported in the first column of Table 3, Panel B include *CBD_DIST* as an additional regressor. The estimated coefficient on *CBD_DIST* is negative and highly significant. Moreover, its inclusion reduces the magnitude of the estimated coefficient on *IXP_DIST* by more than half. However, the coefficient on *IXP_DIST* remains negative and significant at the 5 percent level. Similarly, the estimated coefficients on

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[23] As an additional robustness check, we also re-estimate our main spatial regressions excluding each individual gateway MSA in separate specifications and continue to document a statistically and economically significant effect of *IXP_DIST* on transaction prices in each case. This further mitigates concern that our *IXP_DIST* effect is concentrated in a single large MSA (e.g., New York) or that other linkages common in large metropolitan areas are driving our results.

[24] The mean of *CBD_DIST* is 15.1 miles with a standard deviation of 17.1 miles. At 16.1 and 14.7 miles, respectively, the means of *MSA_DIST* and *LINKAGE_DIST* are similar. The correlation of *IXP_DIST* and *LINKAGE_DIST* is 0.670; the correlation *IXP_DIST* and *CBD_DIST* is 0.434; the correlation of *IXP_DIST* and *MSA_DIST* is 0.263.

MSA_DIST (column 2) and *LINKAGE_DIST* (column 3) are negative and significant at the 1 percent level; nevertheless, the estimated coefficients on *IXP_DIST* remain negative and significant at the 5 percent level. Interestingly, the estimated coefficient on the spatial dependence term and the spatial error term remain positive and significant in all three specifications. Overall, these results suggest that the estimated negative relation between distance to the nearest IXP and transaction prices we document is not likely to be driven by a correlated omitted distance measure.

5.2 Robustness Tests: Subsample Analysis using MSAs without Heavy or Light Rail Infrastructure

An important related literature examines the relation between geographic proximity to intracity railway infrastructure and asset values (e.g., Gupta, Kontokosta, and Van Nieuwerburgh, 2022). Given the likelihood that many MSAs in our sample have well-established transit infrastructure that predate the development of an MSA's internet infrastructure, it is important to further isolate our documented internet infrastructure effect from the well-documented value-oriented effects of transit infrastructure. We utilize data from the Federal Transit Administration's National Transit Database to identify MSAs that did not have heavy or light rail metropolitan commuter infrastructure in place during any year in our sample period.[25] Our search identifies five MSAs: Indianapolis, Kansas City, San Antonio, Tampa, and Richmond. Using property transaction prices for this subsample of MSAs, we re-estimate our main spatial regression of property value on IXP distance. By focusing this robustness test on a subsample of MSAs without railway transit infrastructure, we isolate the value effects of geographic proximity to internet infrastructure from that of public transit.

The fourth column in Panel B of Table 3 displays results from estimating our baseline spatial regression on the subsample of MSAs without heavy or light rail transportation systems. The estimated coefficient on *IXP_DIST* is again negative and highly significant. In fact, the magnitude of the coefficient is almost identical to that of our spatial regression estimated on the full sample of MSAs. This additional result provides strong evidence that

[25] In particular, we examine individual transit agency files for each of our 25 MSAs to determine whether heavy or light rail public transportation is operated within the MSA within a particular year.

our IXP distance effect is unrelated to pre-existing linkages to transportation infrastructure located within the MSA.

5.3 Further Robustness Tests: Property Values and the Establishment of an IXP

Although we focus on property transactions that occur after an IXP has been established, it is possible that the distance effect we document captures a spurious result if this relation existed prior to the establishment of the IXP at its location. Thus, we construct a series of additional tests to examine the impact of IXP establishment on nearby property values.

We begin our event-time analysis by focusing on MSAs for which we have available pricing information in CoStar both prior to and after the first IXP has been established in an MSA. Figure 4 displays average transaction prices per square foot for office properties located within ½ mile of an IXP in three years prior to and after IXP establishment. We observe a significant increase in the price per square foot of asset sales following the establishment of an IXP – rising from an average of $170 per square foot in the three years before the establishment of an IXP to an average of nearly $330 just two years after the IXP is established. Importantly, the pre-trends are relatively flat prior to the IXP establishment, with a sharply identified increase following the IXP establishment date. These findings provide some preliminary evidence of a substantial price premium occurring only after the IXP has been put in place.

We next estimate a multivariate difference-in-difference regression on a subset of 4,835 transactions that occurred in the year prior and the year after the establishment of an IXP. *AFTER* is an indicator variable equal to one if a property transaction occurred in the year following the establishment of an IXP and zero otherwise. If transaction prices are generally higher in the year following the establishment of an IXP, then we would expect the coefficient on *AFTER* to be positive. To isolate properties located closest to the IXP, we create an additional distance measure, *IXP < ½ Mile*, which is an indicator variable denoting whether a property is located within one-half mile of the IXP.

The interaction of our distance variable and *AFTER*, *IXP < ½ mile*AFTER*, captures the effects of being located within one half mile of the IXP location after its establishment. If it is the establishment of an IXP at this location that is associated with the increase in property valuations, then we would expect this interaction term to be positive and significant in our difference-in-difference estimation. Our regression specification includes the set of previously defined controls from our baseline hedonic regression.

Examination of the results in Column 1 of Table 4 reveals that the estimated coefficients on *IXP < ½ Mile* and *AFTER* are not significant. This indicates that proximity to an IXP location is not related to transaction prices prior to the establishment of the IXP and that average transaction prices within an entire MSA are, in general, no different after IXP establishment. However, the interaction term is positive and significant (at the 5% level). Thus, proximity to the IXP location is associated with higher valuations only after the IXP has been established at its current location. Importantly, this additional result further addresses potential concerns that our primary specifications are capturing price effects unrelated to the establishment of the IXP.[26]

It is also possible that the properties sold after the IXP is put in place are fundamentally different than those that transacted prior to its establishment. This could create a potential sample-selection bias in our primary hedonic specification. To address this concern, we estimate a Heckman (1979) two-stage regression that incorporates information on property transactions that occur prior to the IXP being established. The first-stage selection model estimates a probit regression in which *IXP_EXCHANGE*, a dummy variable equal to one for property transactions that occur after an IXP has been established, is the dependent variable. To meet the exclusion restriction of the first stage regression, we include *Δ INTERNET_USAGE*, defined as the annual percentage change in the proportion of the state's population in which the IXPs MSA is located that uses the internet.[27] We posit that the establishment of an IXP should be highly correlated with an increase in the proportion of the population that uses the internet within a particular geographic area. In Column 2 of Table 4, we document a positive and significant coefficient on *Δ INTERNET_USAGE*, thus meeting the exclusion requirement.

Column 3 of Table 4 presents results from the second stage of the Heckman regression. Our variable of interest is again *IXP < ½ Mile.* By including the inverse mills lambda in the

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[26] As an additional robustness check, we construct a similar multivariate difference-in-difference on a subset of repeat sale transactions that occur prior to and after the establishment of an IXP. Focusing on repeat sale transactions allows us to control for differences in property characteristics that may otherwise be present when comparing transactions that occur prior to and after the IXP is in place. In this test, we continue to observe a significant coefficient on the interaction term, further confirming the IXP effect.

[27] Internet usage data is obtained from the National Telecommunications and Information Administration.

second-stage regression, we mitigate concerns of sample selection bias related to both observable and unobservable factors associated with differences in property transactions before and after the establishment of an IXP. The estimated coefficient on *IXP < ½ Mile* is positive and significant at the 1 percent level. This confirms our prior findings that proximity to an IXP is associated with greater property valuation, while controlling for potential sample selection effects.

6. *The Price-Distance Gradient of IXP Proximity*

The use of linear distance (*IXP_DIST*) in our transaction price regressions may be overly restrictive, particularly if tenants of properties located extremely close to the IXP benefit most from improved internet infrastructure proximity (i.e., marginal proximity benefits attenuate at greater distances). Thus, we extend our spatial regression framework by including our set of dichotomous measures that capture distance to the nearest IXP in half mile increments ("buckets"). Properties located more than two miles from the IXP are the omitted case.

We first report results from spatial regressions that replace *IXP_DIST* with *IXP < ½ Mile* in Column 1 of Table 5. The estimated coefficient on *IXP < ½ Mile* is positive (0.224) and highly significant. An office property located within one-half mile of the IXP location is transacting at a price that is 25.2% greater than other property transactions that occur outside of this distance threshold. The economic magnitude of this effect is nearly double the magnitude of the overall pricing impact that we document using *IXP_DIST* and further highlights the importance of proximity to the IXP.

In Column 2 of Table 5 we report results that include all four dichotomous distance measures. The estimated coefficient on *IXP < ½ Mile* remains positive and highly significant. The coefficient on *IXP ½ to 1 Mile* is also positive and significant at the 1 percent level, although its magnitude is just 53 percent of the coefficient on *IXP < ½ Mile*. The magnitude of the coefficient estimate on *IXP 1 to 1½ Mile* further declines but remains positive and highly significant. Finally, the coefficient on *IXP 1½ Mile to 2 Miles* cannot be distinguished from zero. Overall, the results reported in Table 5 strongly suggest that the marginal effect of distance to the nearest IXP on price declines with relative distance.[28]

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[28] To further confirm nonlinearity in the magnitude of an IXP's pricing effect, we extend our spatial regression model to include a nonlinear distance measure. The estimated coefficient on IXP_DIST^2 is positive and highly

6.1 The Price-Distance Gradient of IXP Proximity by MSA

The results presented so far control for differences in price levels across the 787 sub-markets, and therefore the 25 MSAs, in our sample of transaction prices. However, by aggregating observations, we are forcing the coefficient estimates on our distance measures to be the same across all MSAs. Figure 5 plots estimated coefficients from spatial regressions of price on linear distance to the nearest IXP at the individual MSA level. Panel A displays estimated coefficients for all MSAs and a trendline depicting the average effect across MSAs. The x-axis values depict indicator variables equal to one if the property transaction occurred within one-half mile (0.5), between one-half mile and one mile (1), between one mile and one and one-half mile (1.5), or between one and one-half mile and two miles (2), respectively, from the location of the nearest IXP.

As expected, the estimated coefficients on our dichotomous distance measures vary across the 25 MSAs. However, we observe that transaction prices generally decline as distance to the nearest IXP increases. Panel B displays the distance coefficients for two sample MSAs: New York (NY) and Portland (OR). In New York, we observe a much steeper slope in the relation between distance and price. A comparison of these two series suggests that both the magnitude and gradient of the pricing effect is greater in New York than Portland. Overall, these MSA level results support the conclusion that the need for internet speed is reflected in the transaction prices of U.S. office properties. However, as expected, the magnitude and rate of decay of this effect varies across MSAs.

7. The Tenant-based Channel of the IXP Pricing Effect

If the supply of office space surrounding an IXP is relatively fixed, at least in the short run, we expect the heightened valuations of properties close to the IXP to reflect, in part, higher rents being paid by tenants that value the property's geographic proximity to an IXP. Furthermore, the tenants most likely to benefit from, and thereby most willing to pay for, proximity to an IXP are likely KTI firms. Taken together, this suggests a possible tenant-based channel for our IXP pricing effect.

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significant, indicating a non-linear relation between distance to the nearest IXP and transaction prices. Thus, properties closer to the IXP experience a greater magnitude impact on property valuation associated with the establishment of an IXP nearby. Furthermore, the estimated coefficient on *IXP_DIST* increases in magnitude from 0.018 to 0.025, which further suggests that our linear specifications may tend to understate the magnitude of the pricing effect for properties in proximity to the IXP.

To validate the existence of a tenant-based channel of IXP pricing, we incorporate a second dataset (CompStak) into our analysis that provides information on individual lease transactions within single and multi-tenant office buildings including rent, lease characteristics, and tenant composition data. These data allow us to explore the tenant-base of our property-level analysis as well as further examine the relationship of agglomeration and commercial rents.[29] The tenant-based channel has two primary implications for our valuation analysis: (1) we should observe higher effective rents in office properties surrounding an IXP, and (2) the impact of IXP distance on observed rents should be greater for tenants working in KTI industries given their expected increased willingness to pay for proximity to an IXP.

7.1 Lease Transaction Data

Lease transaction data is provided by CompStak, a crowdsourced CRE data platform that collects and reports data on commercial rents and lease characteristics for over 100 metropolitan markets.[30] Our focus remains on office properties located in the 25 MSAs included in our analysis of sale prices. Our original CompStak dataset contains 376,390 analyst-verified office lease transactions that occurred from January 1999 to December 2019.

We require the following information for a lease observation to be included in our final sample: property street address, city, state, zip code, latitude, longitude, structure age, building square footage, land square footage, number of floors, building class, lease type (new, renewal, or sublease), square footage of leased space, tenant's responsibility for building-level operating expenses, lease execution date, lease term, and the effective per square foot rental rate. This reduces our sample to 139,756 lease observations. After removing transactions that occurred before the establishment of an IXP within the MSA, our final regression sample consists of 83,265 lease observations.

Panel A of Figure 6 displays the distribution of lease observations across our 25 MSAs. Over 60 percent are in the six gateway markets, with the largest number observed in the Los Angeles metropolitan market (15,757). Non-gateway markets with the highest number of

[29] Recent work by Liu, Rosenthal, and Strange (2018), Gupta et al., (2021), and Rosenthal, Strange, and Urrego (2022) highlight the important link between rents and agglomeration.

[30] As a crowdsourced data platform, commercial leasing agents are permitted to access a specified number of comparable lease transactions in the CompStak database in exchange for every comparable lease transaction the agent contributes to the database. All lease observations are analyst-reviewed by CompStak for accuracy and completeness.

lease observations include Dallas (7,003), Atlanta (4,872), Seattle (4,216), Philadelphia (2,889), and Phoenix (2,672). Only three MSAs have less than 300 lease observations (Pittsburgh, Richmond, and St. Louis).

Table 6 presents summary statistics for our final lease sample. The mean (median) distance between lease observations and the nearest IXP (*IXP_DIST*) is 4.7 (1.9) miles. Approximately 20 percent of our lease observations are from properties located within one-half mile of the IXP, 17 percent are from properties located between one-half mile and one mile, while about 14 percent are between a mile and two miles of the nearest IXP. Slightly less than 50 percent of the lease transactions are more than two miles from the nearest IXP.

We next report summary statistics on the following property-level characteristics defined previously: *AGE, BLDG_SQFT, LAND_SQFT, FLOORS, CLASS A, CLASS B,* and *CLASS OTHER*. The average office property in our lease sample is 39 years old, contains 383 thousand square feet of leasable space, and is built on a 138 thousand square foot land parcel. The average (median) office property contains 16.5 (11.0) floors. Most lease transactions involve "Class A" properties (72 percent); 26 percent of the sample properties are classified as "Class B."[31] Thus, CompStak's lease data appear to be more reflective of transactions involving "institutional quality" properties than our CoStar transaction price sample.

We also employ a series of lease characteristics available in the CompStak data. Our main variable of interest is the annualized effective per square foot rental rate, which we denote as *RENT*. CompStak defines *RENT* as the annualized starting rent per square foot that is adjusted upward to capture estimated building-level operating expenses for which the tenant is responsible for paying to an entity other than the landlord. *RENT* is also adjusted downward by CompStak to capture landlord concessions to the tenant and upward to reflect scheduled rent increases over the lease term. Thus, *RENT* is an estimate of the tenant's "effective" rental rate. The mean value of *RENT* is $34 per square foot per year. We utilize the natural log of *RENT* (*LN_RENT*) in our empirical analysis.

We also include the amount of the tenant's leased space (*SPACE_SQFT*), lease term in months (*TERM*), transaction type (*NEWLEASE*, *RENEWAL* or *SUBLEASE*) and variables that characterize who pays building-level operating expenses (*GROSS*, *TRIPLENET*, or *NET*). The average lease involves approximately 13 thousand square feet of leased space and has a term of approximately five years (66 months). Most leases are new

[31] Construction type and property condition variables are not available in the CompStak data.

originations (59%); 35 percent are renewals and only 6 percent are subleases. In our sample, 82 percent of office leases are "gross" leases in which the landlord pays all building-level operating expenses. However, 11 percent of our sample leases are "triple net" leases in which the tenant pays a share of all building-level operating expenses by reimbursing the owner or by paying the amount owed directly to third party service providers (e.g., utility companies and hazard insurers) and others (e.g., local property tax collectors). Approximately 8 percent of sample leases are "net" leases (*NET*) in which the tenant pays its share of property taxes and hazard insurance.[32]

Since rental rates may also vary by their vertical orientation (e.g., Liu, Rosenthal, and Strange, 2018), we also include several indicator variables depicting the relative location of the leased space within an office building. *HIGH_FLOOR*, *MID_FLOOR*, and *LOW_FLOOR* are indicator variables denoting leased space located in the upper third, middle third, or lower third of a building, respectively. *FLOOR_NA* is an indicator variable set equal to one if the floor number is not available in CompStak's database, and zero otherwise. Approximately 17 percent of our leases are concentrated in the upper third of a building, 20 percent are from the middle third, and 19 percent pertain to lower floors. Slightly less than 45 percent of lease observations have no floor information available.

7.2 IXP Distance and Effective Rents

Since our lease data contains multiple observations pertaining to a single geographic location, generating spatial weight matrices based on distance to a centralized location is not possible, thus prohibiting the use of spatial regressions in our rent analysis. Thus, our baseline semi-log hedonic rental rate regression model has the following form:

$$
\begin{aligned}
LN\_RENT_i = {} & \phi + \lambda_1 IXP\_DIST + \lambda_2 AGE + \lambda_3 AGE^2 + \lambda_4 BLDG\_SQFT + \lambda_5 BLDG\_SQFT^2 \\
& + \lambda_6 LAND_{SQFT} + \lambda_7 {LAND_{SQFT}}^2 + \lambda_8 FLOORS + \lambda_9 LONG + \lambda_{10} LAT \\
& + \lambda_{11} SPACE\_SQFT + \lambda_{12} TERM + \lambda_{13} RENEWAL + \lambda_{14} SUBLEASE \\
& + \lambda_{15} TRIPLENET + \lambda_{16} NET + \lambda_{17} HIGH\_FLOOR + \lambda_{18} MID\_FLOOR \\
& + \lambda_{19} FLOOR\_NA + \lambda_t T + \lambda_r R + \lambda_s S \\
& + \varepsilon_m \qquad (4)
\end{aligned}
$$

[32] CompStak uses a multi-step heuristic approach to upward adjust renal rates on triple net lease properties to reflect building-level operating expenses expected to be paid by the tenant to a third party. *RENT* does not capture the timing of rental inflows or outflows.

Property and lease characteristics are defined above.[33] The inclusion of building latitude and longitude coordinates, as well as Compstak's submarket classifications, as control variables in our hedonic regression mitigates the impact of unobservable local characteristics on our documented IXP effect.

Table 7 presents estimates from hedonic regressions of effective rent (*LN_RENT*) on the lease transaction's linear distance to the nearest IXP, property characteristics, and lease characteristics. The estimated coefficient on *IXP_DIST* is negative and highly significant (Column 1 of Table 7). A one standard deviation increase in *IXP_DIST* is associated with a 3.2 percent decrease in *LN_RENT*. Effective rental rates are negatively related to *AGE*, although the relation decreases with age. Per square foot rental rates are positively related to *BLDG_SQFT*, although this relation is also nonlinear. Unlike transaction prices, rental rates do not appear to be associated with the square footage of the land; however, the estimated coefficient on *FLOORS* is positive and highly significant. This result is consistent with the findings of Liu, Rosenthal and Strange (2018) and the expectation that the value of office views increases with height.

Turning next to the characteristics of the lease, we find a negative and significant relation between the square footage of leased space and the effective per square foot rental rate. This "quantity discount" is consistent with the landlord's fixed costs of lease execution and ongoing administration. In contrast, the estimated coefficient on *TERM* is positive and highly significant which suggests landlords generally prefer the flexibility associated with shorter lease terms. Our expectation is that renewing tenants can negotiate lower rental rates than new tenants given that landlords typically incur lower refurbishing costs when an existing tenant maintains occupancy of the space. However, when using new leases as the omitted case, the estimated coefficient on *RENEWAL* is positive and highly significant. This may indicate that renewals occur more frequently on higher-quality properties. In contrast, the estimated coefficient on *SUBLEASE* is negative and highly significant. This result may reflect the inferiority of subleased space not controlled for by the property's characteristics or the other lease characteristics included in the regression model. This result may also reflect

[33] CompStak and CoStar have distinct property subtype and geographic submarket classification categories. CompStak includes 21 unique property subtype classifications in our office dataset. However, this variable is only populated in approximately 12 percent of our lease observations. There are 447 distinct CompStak delineated geographic submarkets across our 25 MSAs, or an average of 18 submarkets per MSA.

the relatively weak bargaining position many tenants find themselves in when they are attempting to sublease some, or all, of their office space.

Although CompStak adjusts for differences in the treatment of operating expenses in their calculation of effective rental rates, we include dummy variables that indicate if the lease is a triple net (*TRIPLENET*) or net (*NET*) lease. The inclusion of these dummy variables helps to control for omitted lease characteristics correlated with lease type. As expected, leased space in the upper third of an office building (*HIGH_FLOOR*) commands significantly higher rents than space in the lower third of the building; rents in the middle third cannot be distinguished from rents in the lower part of the building. Our hedonic regression model explains 69 percent of the variation in effective rental rates.

We next re-estimate our regression model after replacing linear distance to the IXP with the dummy variable *IXP < ½ Mile*. These results are reported in column 2 of Table 7. The estimated coefficient on *IXP <½ Mile* is positive and significant at the 5 percent level. Leases executed on office properties located within one-half mile of the IXP location are transacting at an annual effective rent per square foot that is 1.0% greater than other lease transactions that occur outside of this distance threshold. This reinforces our finding that rent determining tenants are willing to pay for proximity to IXPs.

To further investigate the extent to which rents decline with distance to the nearest IXP, we again use our dichotomous measures that capture distance in half mile increments. The omitted distance category is greater than two miles from the nearest IXP. These results are reported in column 3 of Table 7.

The estimated coefficient on *IXP <½ Mile* remains positive and highly significant and increases in magnitude relative to the results reported in column 2. The estimated coefficient on *IXP ½ to1 Mile* is positive but only significant at the 10 percent level and the estimate on *IXP 1 to 1½ Mile* cannot be distinguished from zero. Taken together, these results strongly suggest that the marginal effect of distance to the nearest IXP on rents declines with relative distance. Interestingly, the coefficient estimate on *IXP 1½ to 2* Miles is negative and significant, indicating lower rents for tenants in offices located at this distance relative to those located more than 2 miles away from the IXP. This unexpected result suggests that there may be a distance threshold at which other unobserved property linkages become relatively more important in determining the rents of tenants located in properties further away from the IXP.

As discussed above, distance to the nearest IXP may be correlated with distance to other rent-determining MSA features. For robustness, we therefore separately include the previously defined alternative distance measures and re-estimate our effective rental rate models. The results are reported in Panel A of Appendix A. The estimated coefficients on *CBD_DIST*, *MSA_DIST*, and *LINKAGE_DIST* are all negative and highly significant. Furthermore, their inclusion reduces the magnitude of the estimated coefficients on *IXP_DIST*. However, the coefficient on *IXP_DIST* remains negative and significant at the 5 percent level or greater. These results suggest that the estimated negative relation between distance to the nearest IXP and effective rental rates reported in Table 7 is not driven by a correlated omitted distance measure.

Because it is also possible that distance to the nearest IXP is corelated with characteristics of the broader MSA in which the leased office space is located, we separately include the previously defined MSA characteristics and re-estimate our effective rental rate models. These results are reported in Panel B of Appendix A. Each of these indicator variables is also interacted with *IXP_DIST* to determine if inclusion of the MSA characteristic affects the estimated coefficient on *IXP_DIST*. In each specification we continue to document a significant negative relation between IXP distance and effective rents. These results strongly suggest that our rent results are not driven by omitted MSA characteristics that are correlated with distance to the nearest IXP.

7.3 Tenant Composition, IXP Distance and Effective Rents

To test our hypothesis that tenants involved in technology intensive industries are more willing to pay for proximity to an IXP, we extend our lease-level analysis to consider the impact of tenant industry composition on rents. We utilize the tenant's industry classification code (NAICS code) in CompStak's database to identify lease transactions that involve a KTI tenant. We classify a firm as a "KTI" tenant if it if has one of the following NAICS codes: High Technology (Services), Knowledge Creation, Information Technology, Knowledge-Based (Professional Services) or Knowledge-Based (Financial Services).[34] We then construct *KTI_TENANT*, an indicator variable equal to one if the tenant is from a KTI industry category, and zero otherwise.

[34] KTI industry classifications are derived from several sources including the Organization of Economic Cooperation and Development (OECD) and the U.S. Bureau of Labor Statistics. Individual NAICS codes corresponding to each industry classification are detailed in Appendix B.

Approximately 39 percent of our lease sample involves tenants from KTI industries (Table 6). However, the proportion of KTI tenants varies across MSAs. Panel B of Figure 6 displays the distribution of lease observations across the 25 MSAs that we track, disaggregated by whether the tenant is from a knowledge and technology intensive industry. The six gateway cities tend to have a higher proportion of leases attributed to KTI tenants than non-gateway markets. At 52 percent, San Francisco has the highest concentration of KTI tenants. In all 25 MSAs, KTI tenants represent at least 25% of lease transactions.

To further motivate a tenant-based channel for our IXP pricing effect, we first examine the change in tenant composition around the establishment of an IXP in a MSA. This subsample analysis focuses on MSAs for which we have available lease information in CompStak both prior to and after the first IXP has been established in an MSA. Figure 7 displays the proportion of KTI tenants located within ½ mile of an IXP in the years prior to and after IXP establishment. We observe a significant increase in the proportion of KTI tenants following the establishment of an IXP – rising from an average of 36% two years before the establishment of an IXP to an average of nearly 42% just two years after the IXP is established, an economically significant 17 percent increase. Importantly, the pre-trends are relatively flat prior to the IXP establishment, with a sharply identified increase following the IXP establishment date. These findings provide some preliminary evidence of an agglomeration effect that is consistent with our conjecture of a demand driven KTI-based channel for an IXP price premium.

Further exploring the link between agglomeration and commercial rents, we next examine the impact of KTI tenant composition on rents in office space located within close proximity to the IXP. Table 8 presents estimates from hedonic regressions of effective rent on distance to an IXP, property characteristics, and lease characteristics, including KTI tenant classification. Building class dummies, year fixed effects, sub-property type dummies and submarket dummies are included in all specifications. In the first two columns, we report results using our liner distance measure (*IXP_DIST*). In the last two columns we provide results estimated using *IXP < ½ Mile* in place of *IXP_DIST*.

The estimated coefficient on our *KTI_TENANT* dummy variable in the first column is positive and highly significant, indicating that KTI tenants pay significantly higher rents than other tenants. However, the estimated coefficient on *IXP_DIST* remains negative and highly significant. In our second specification, we add an interaction term, *IXP_DIST*KTI_TENANT*. This addition does not materially alter the magnitude or significance of the *IXP_DIST* coefficient; however, we document a negative and highly significant coefficient on *IXP_DIST*KTI_TENANT*, indicating a stronger effect of IXP distance on effective rental rates among KTI tenants.

The substitution of *IXP < ½ Mile* for *IXP_DIST* has no effect on the magnitude or significance of the coefficient estimate on *KTI_TENANT*. In addition, the estimated coefficient on *IXP<½ Mile* is positive and significant at the 5 percent level. In the fourth column of Table 8, we report results from a regression in which we add an *IXP<½ Mile*KTI_TENANT* interaction term. This addition reduces the estimated coefficient on *KTI_TENANT* from 0.019 to 0.016, although it remains significant at the 1 percent level. Importantly, the estimated coefficient on the interaction term is positive and highly significant, indicating a stronger positive effect of close proximity to the nearest IXP on rental rates among KTI tenants. In fact, the magnitude of the coefficient on the interaction term is approximately 1.5 times greater than the stand-alone coefficient on *IXP<½ Mile* in column 3.

7.4 The Rent-Distance Gradient of IXP Proximity by MSA

Figure 8 plots estimated coefficients from hedonic regressions of effective rents on distance from an IXP at the individual MSA level for leases involving tenants from KTI industries. We display statistically significant estimated coefficients as well as a trend line depicting the average effect across MSAs. The x-axis values depict distance to the nearest IXP in half-mile increments. As expected, the estimated coefficients on distance measures vary across the MSAs. However, we do observe that rental rates generally decline as distance to the nearest IXP increases, which supports the conclusion that the need for internet speed is reflected in the rental rates negotiated by tenants and landlords.

8. Summary and Conclusions

The price premium associated with the demand for office space and the concentrated supply of office properties in major metropolitan markets is often viewed as a function of a property's amenities and its spatial linkages. A large agglomeration literature suggests that a property's spatial linkages include its geographic proximity to employee talent, clients, competitors, and transportation hubs. However, as technology infrastructure has advanced, the desire to be located close to a point of Internet connectivity has emerged. Over the past two decades major metropolitan markets have become central locations for the exchange of information on the internet's physical infrastructure. Given the increased volume of internet traffic in these markets, the desire for information transmission speed has become an important consideration for many office tenants. This "need for speed" has the potential to create value premiums for properties located closest to these points of internet access. Our findings highlight the financial and agglomeration effects arising from the establishment and geographic placement of internet infrastructure.

Using an extensive hand collected dataset of U.S. internet exchange points (IXPs) and office property transaction data from CoStar for the period spanning January 1999 through December 2019, we examine the impact of distance to the nearest IXP on transaction prices in 25 major U.S. metropolitan markets. We first estimate a semi-log hedonic regression model and find that a one standard deviation increase in linear distance to an IXP is associated with a 13 percent decrease in sale price.

We extend our basic hedonic regression framework to account for potential spatial dependence between commercial property transactions by estimating a spatial autoregressive (SARAR) model. We find that distance is still negatively related to transaction prices; however, the significance of the estimated spatial dependence term and the spatial error term suggest that the transaction prices of properties in our office sample in close proximity to each other incorporate exposures to a common set of value determinants not included in our hedonic regression specification. Importantly, the economic magnitude of the price premium nearly doubles for properties located less than ½ mile to an IXP relative to those located outside of this threshold; however, the effect is insignificant at distances greater than 1½ miles from an IXP. Our documented pricing results are robust to controlling for numerous other potential important spatial linkages and MSA characteristics. A battery of additional robustness and identification tests, including a multivariate difference-in-difference regression and subsample tests, further confirm our documented IXP location pricing effects.

We next examine a tenant-based demand channel to help explain the pricing premium. If the supply of office space surrounding an IXP is relatively fixed, at least in the short run, we expect the heightened valuations of properties close to the IXP to reflect, in part, higher rents being paid by building tenants that value the property's geographic proximity to an IXP. In addition, the impact of IXP distance on observed rents should be greater for tenants working in knowledge and technology intensive (KTI) industries given their expected increased willingness to pay for proximity to an IXP. Our examination of a tenant-based channel of IXP pricing requires granular lease data; we therefore incorporate data from CompStak into our analysis. These data include detailed information on individual lease transactions within single and multi-tenant office buildings, including rent, lease characteristics, and tenant composition data.

Consistent with our property pricing results, we find that distance to an IXP has a significant effect on rents paid. We also find an economically significant 17% increase in the percentage of KTI tenants operating near an IXP following its establishment. This finding highlights the agglomeration (clustering) effects that accompany these important additions of internet infrastructure within a geographic location. Moreover, the impact of IXP distance on rents is greater for tenants working in KTI industries. Taken together, our transaction price and rent results underscore the important interplay among internet infrastructure location, real asset location, agglomeration, and valuation effects.

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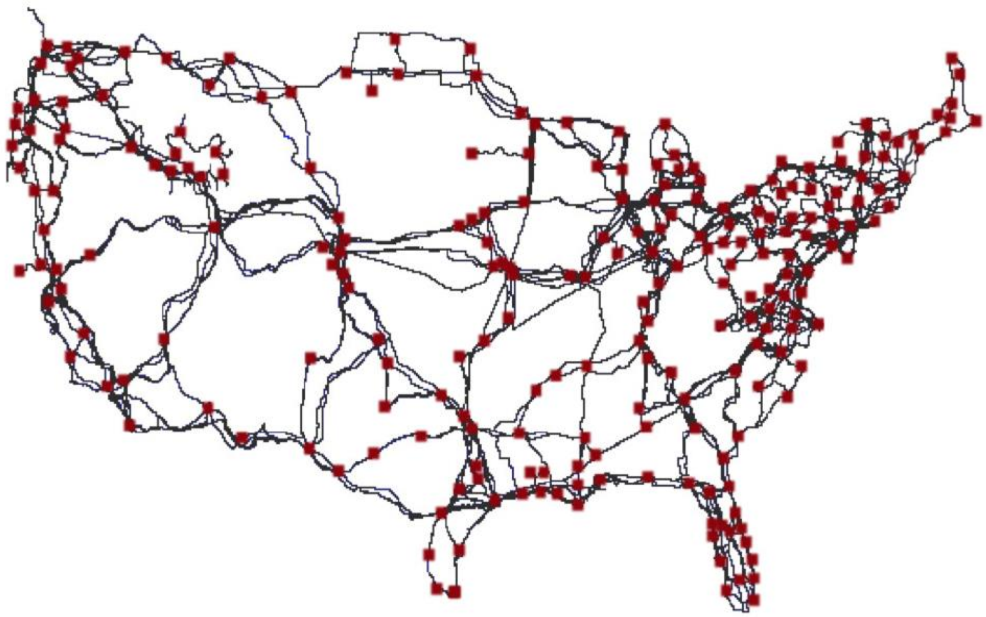
Figure 1: Internet Exchange Point Maps

This figure plots the geographic infrastructure of the internet (Panel A) and the subsample of internet exchange points for which an IXP's establishment year has been identified (Panel B).

Panel A – Internet Infrastructure



Source: Durairajan, Barford, Sommers and Willinger (2015)

Panel B – Internet Exchange Point Sample

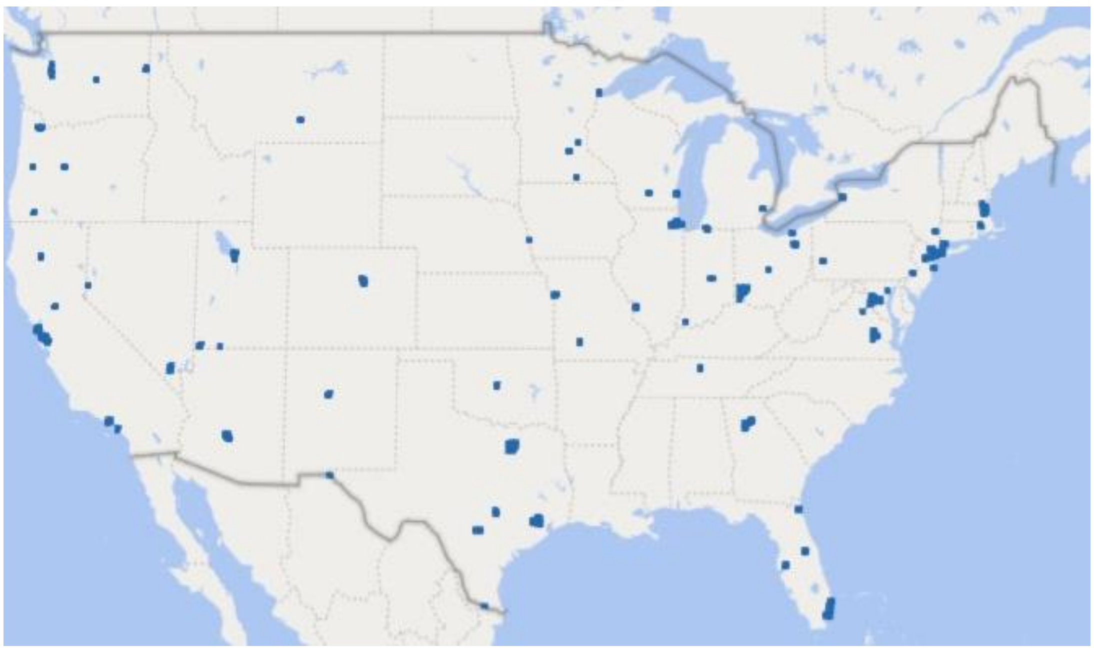
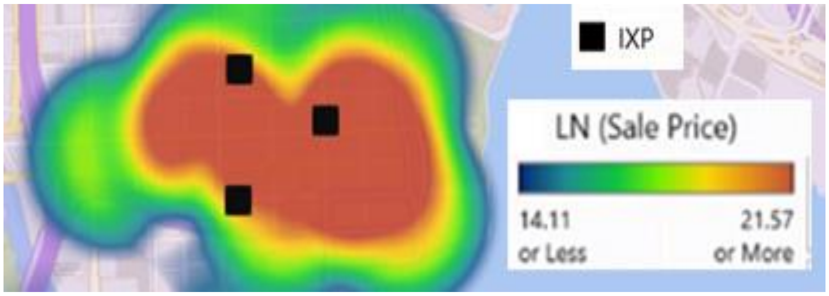


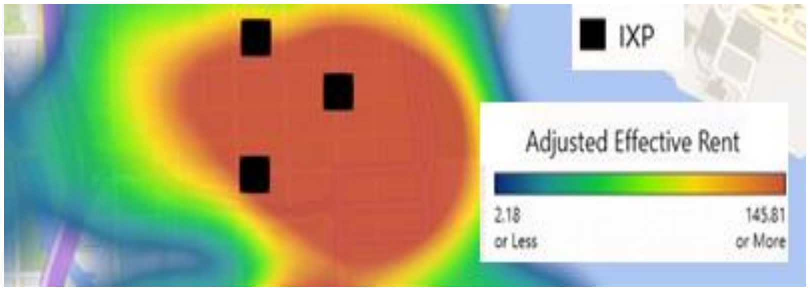
Figure 2: Property Values, Rents, and Tenant Composition Around an IXP

This figure displays a sample heat map of the relation between the property's distance from an internet exchange point (IXP) and property transaction prices (Panel A), effective rents (Panel B), and the amount of leased space by tenants from Knowledge and Technology Intensive (KTI) industries (Panel C).

Panel A – Property Value and IXP Location – Miami, FL



Panel B – Effective Rents and IXP Location – Miami, FL



Panel C – Knowledge & Technology Intensive (KTI) Tenants and IXP Location – Miami, FL

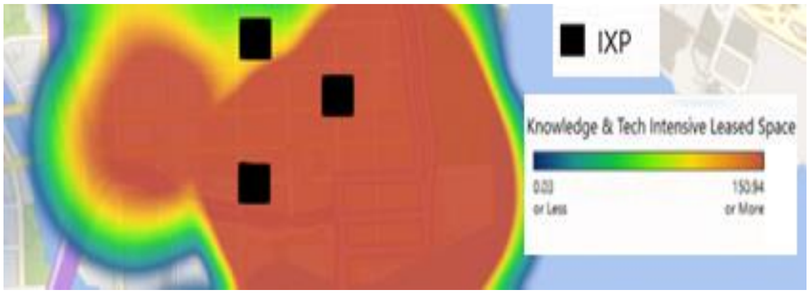
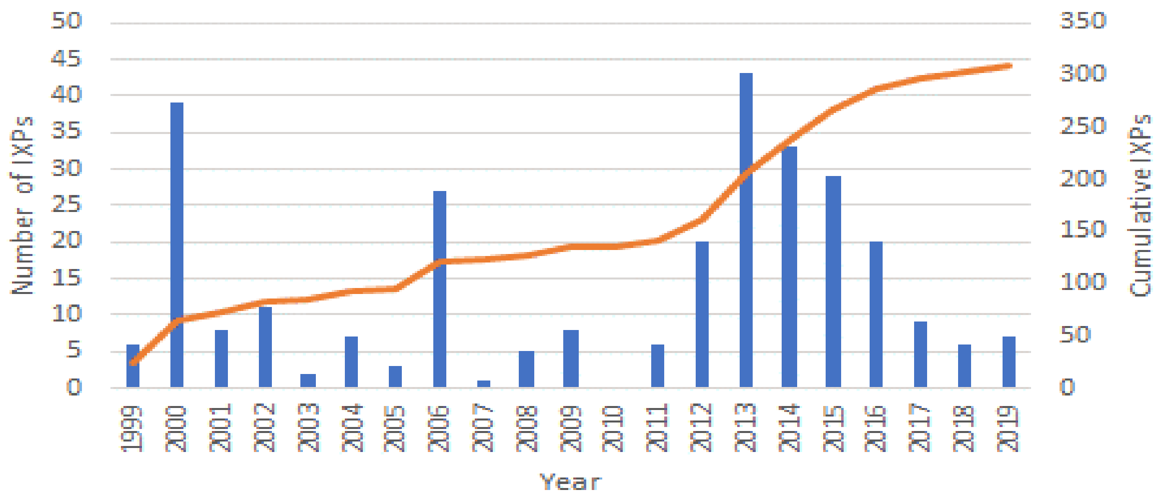


Figure 3: Sample Distribution of Internet Exchange Points by Year and Location

This figure plots the sample distribution of internet exchange points (IXPs) by year (Panel A) and location (Panel B). Year is the year in which the IXP was established. Location is defined at the Metropolitan Statistical Area (MSA) level. The sample period is 1999-2019.

Panel A – Distribution of Internet Exchange Points by Year Established



Panel B – Distribution of Internet Exchange Points by MSA

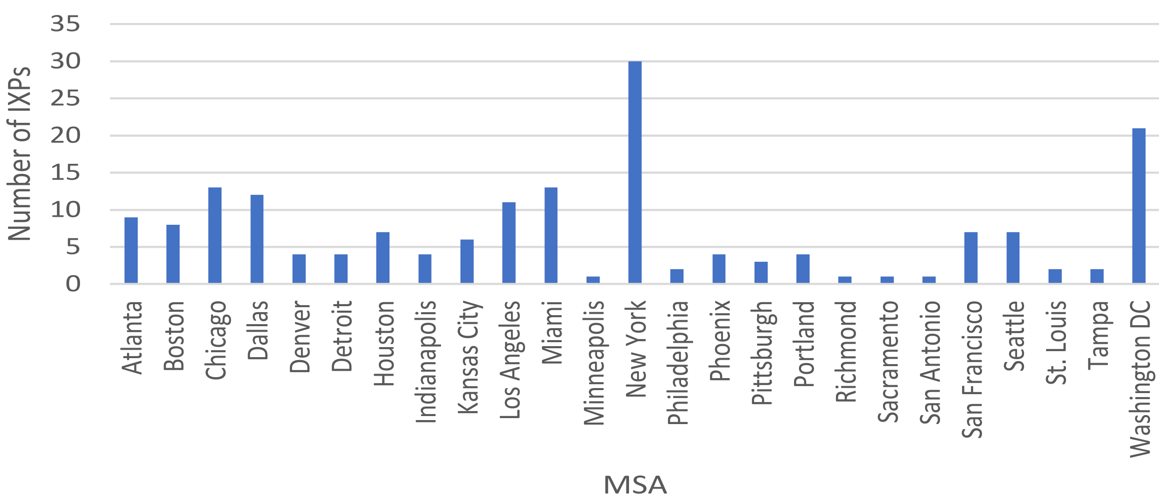


Figure 4: Property Values around IXP Establishment

This figure plots the average sale price per square foot of an office property transaction located within ½ Mile of an internet exchange point (IXP) in event time around the IXP's establishment. Transaction price data is obtained from CoStar. The sample period is 1999-2019.

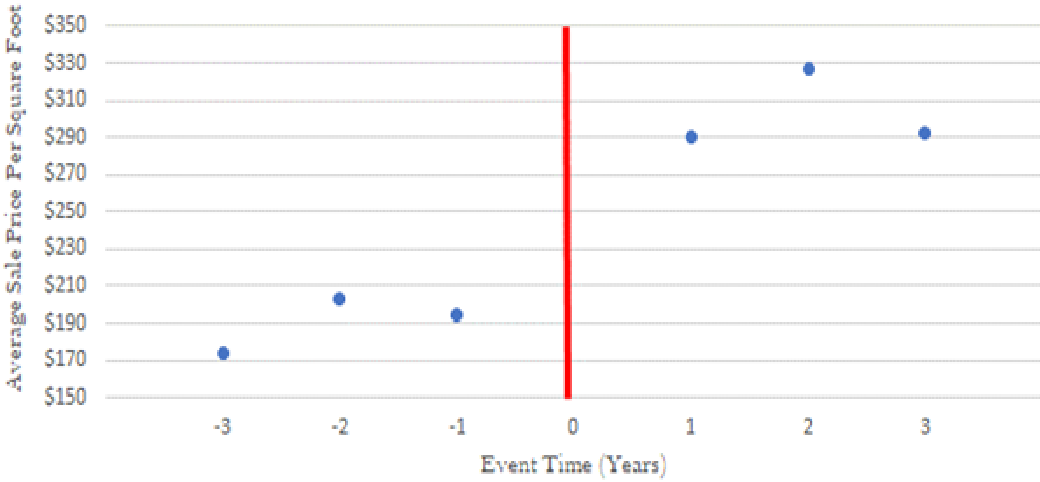
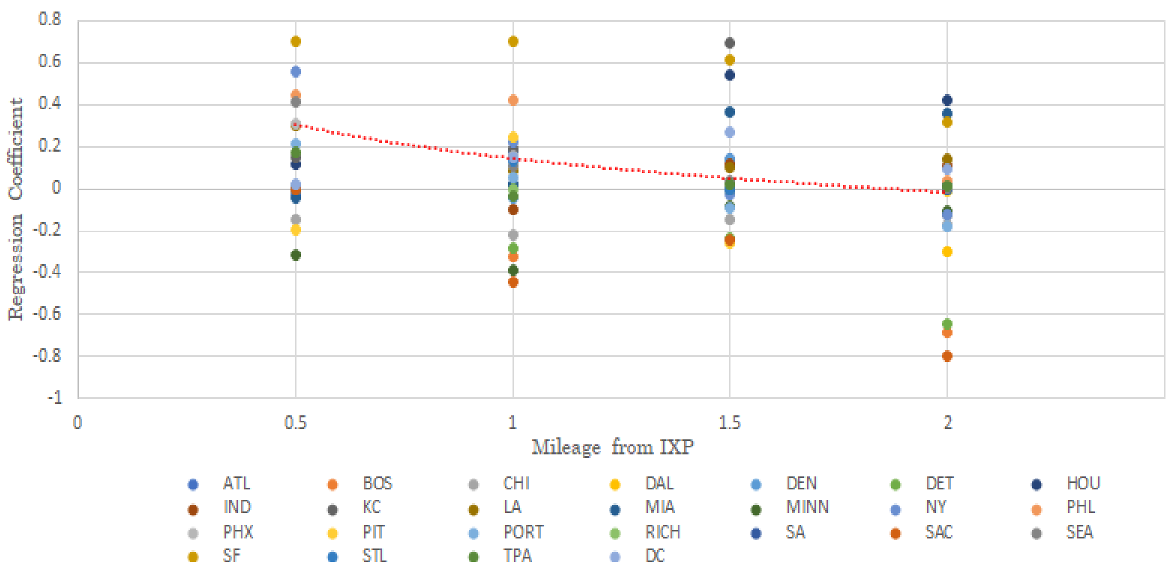


Figure 5: Price – IXP Distance Gradient by Metropolitan Statistical Area (MSA)

This figure plots estimated coefficients from spatial regressions of price on distance from an internet exchange point (IXP) at the individual MSA level. Panel A displays estimated coefficients for all MSAs and a trend line depicting the average effect across MSAs. Panel B displays coefficients for two sample MSAs: New York (NY) and Portland (OR). The x-axis values depict indicator variables equal to one if property transactions that occur within less than one-half mile (0.5), between one-half mile and one mile (1), between one mile and one and one-half mile (1.5), and between one and one-half mile and two miles (2), respectively, from the location of the internet exchange point (IXP). The sample period spans 1999-2019.

Panel A – Price-IXP Distance Gradient (All MSAs)



Panel B – Price-IXP Distance Gradient (New York vs. Portland)

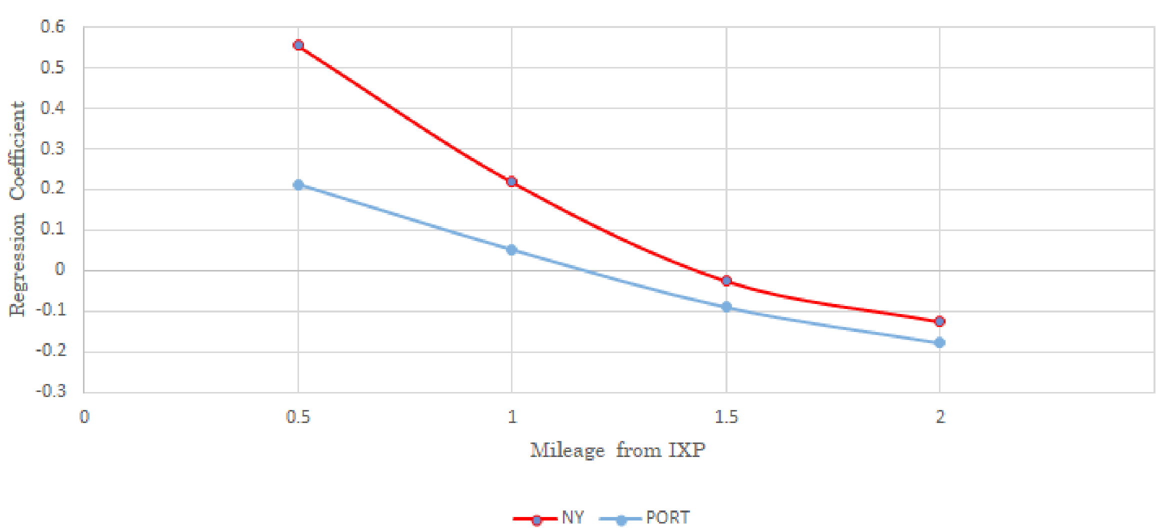
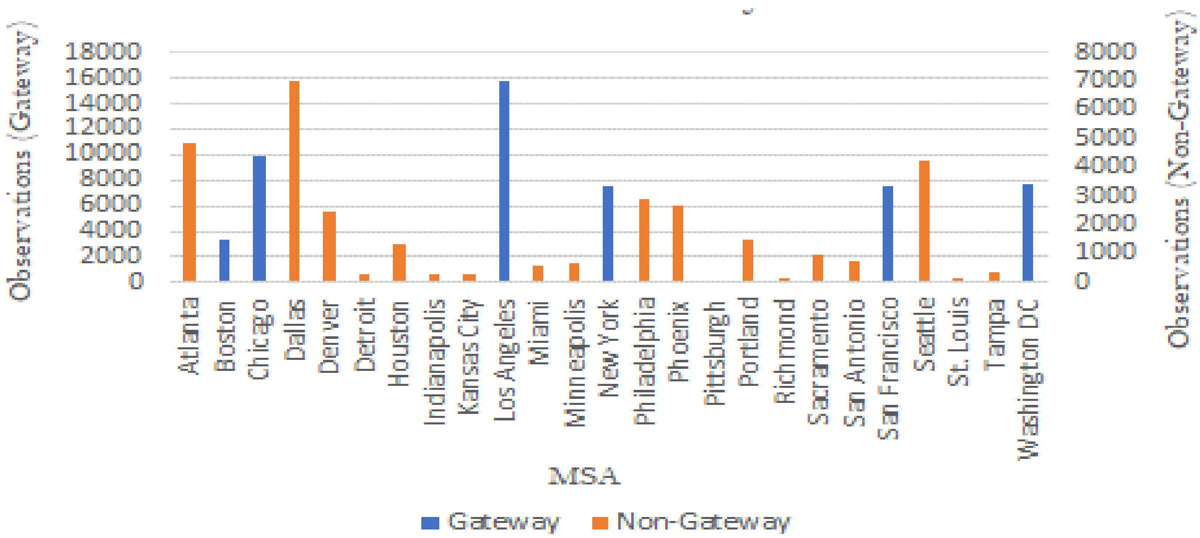


Figure 6: Sample Distribution of Lease Data by Location and KTI Industry Classification

This figure plots the sample distribution of leases by location (Panel A) and KTI Industry Classification (Panel B) . Location is defined at the Metropolitan Statistical Area (MSA) level and disaggregated into gateway and non-gateway markets. KTI Industry classifications are defined in Appendix B. Lease data is obtained from CompStak. The sample period is 1999-2019. N is 83,265 observations.

Panel A – Distribution of Leases by MSA



Panel B – Distribution of Leases by MSA and KTI Classification

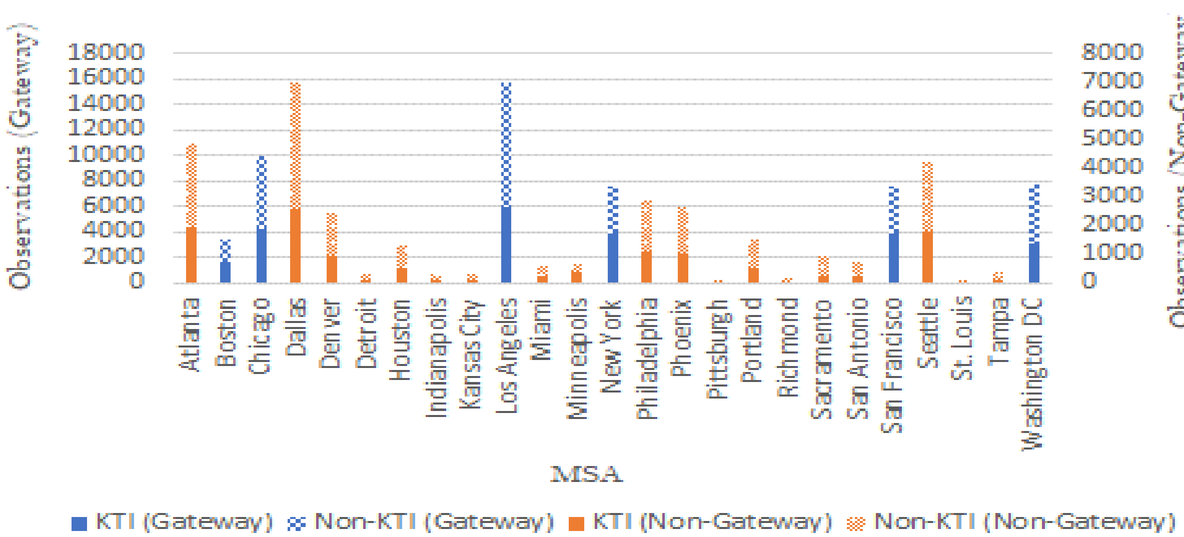


Figure 7: Knowledge & Tech Intensive (KTI) Concentration Around IXP Establishment

This figure plots the average proportion of lease contracts that are executed by tenants from Knowledge and Technology Intensive (KTI) industries located within ½ mile of an internet exchange point (IXP) in event time around the establishment of an IXP. KTI Industry classifications are defined in Appendix B. Lease data is obtained from CompStak. The sample period is 1999-2019.

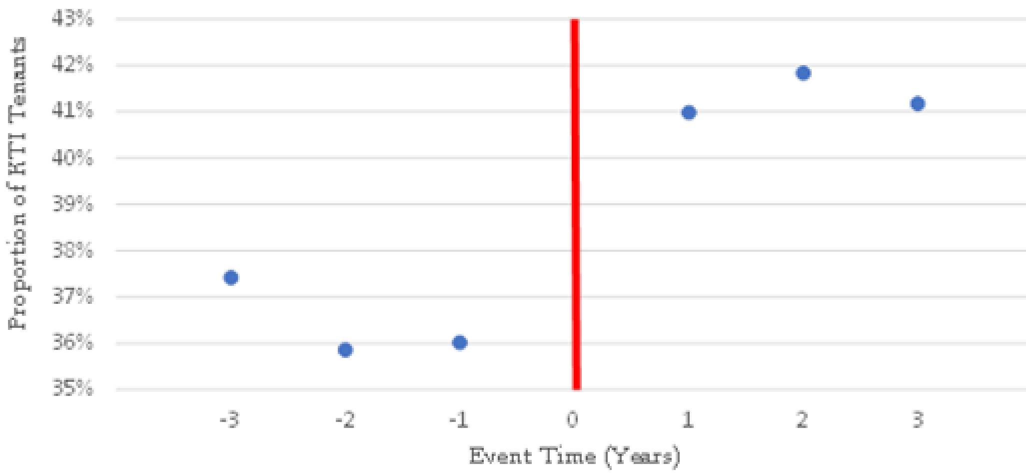


Figure 8: Rent-IXP Distance Gradient by MSA – Knowledge & Tech Intensive (KTI) Tenant

This figure plots estimated coefficients from hedonic regressions of the natural log of adjusted effective rent on distance from an internet exchange point (IXP) at the individual MSA level for leases involving tenants from Knowledge and Technology Intensive (KTI) industries. Estimated coefficients that are statistically significant are displayed for all MSAs, as well as a trendline depicting the average effect across MSAs. The x-axis values depict indicator variables equal to one if property transactions that occur within less than one-half mile (0.5), between one-half mile and one mile (1), between one mile and one and one-half mile (1.5), and between one and one-half mile and two miles (2), respectively, from the location of the internet exchange point (IXP). The sample period spans 1999-2019.

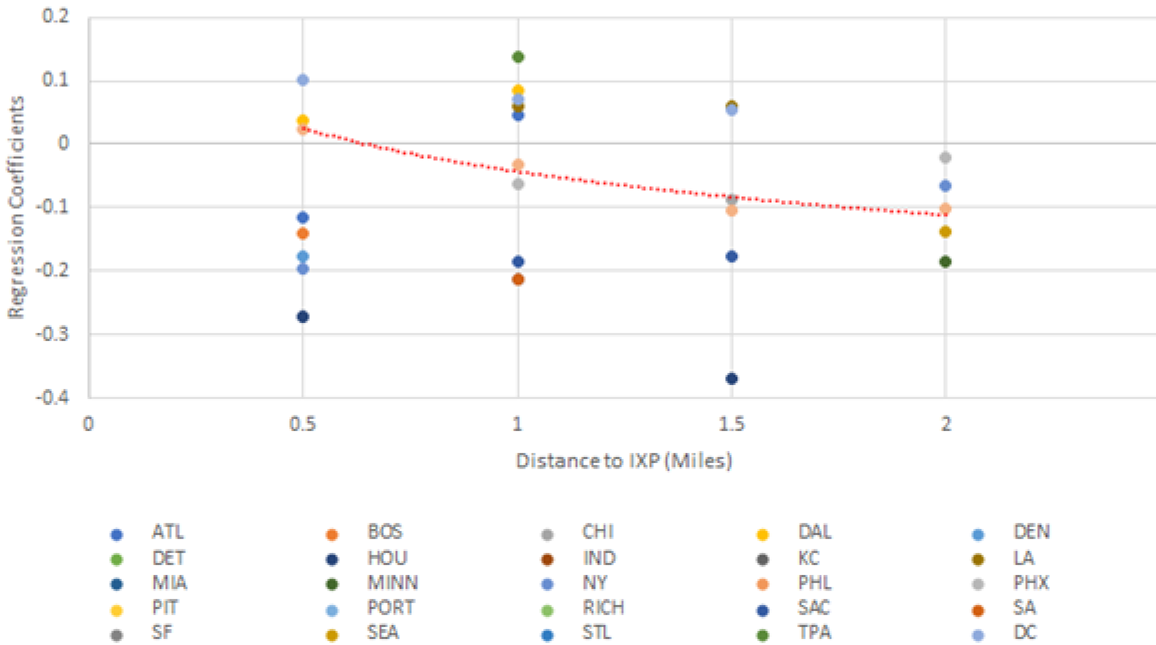


Table 1: Descriptive Statistics – Property Characteristics

This table presents descriptive statistics for property characteristics. *IXP_DIST* is the distance in miles between the property transaction and the location of the internet exchange point (IXP). *IXP<½ Mile* is an indicator variable denoting whether a property is located less than one-half mile from the location of the internet exchange point (IXP). *IXP ½ Mile to 1 Mile* is an indicator variable denoting whether a property is located between one-half mile and one mile from the location of the internet exchange point (IXP). *IXP 1 Mile to 1½ Mile* is an indicator variable denoting whether a property is located between one mile and one and one-half mile from the location of the internet exchange point (IXP). *IXP 1½ Mile to 2 Miles* is an indicator variable denoting whether a property is located between one and one-half mile and two miles from the location of the internet exchange point (IXP). *IXP > 2 Miles* is an indicator variable denoting whether a property is located more than two miles from the location of the internet exchange point (IXP). *PRICE* is the nominal sale price in millions USD. *LN_PRICE* is the natural log of the sale price in USD. *AGE* is the age of the property in years. *BLDG_SQFT* is the total square footage of improvements in thousands of square feet. *LAND_SQFT* is the total square footage of land in thousands of square feet. *FLOORS* is the number of floors in an office property. *CLASS_i* is an indicator variable denoting property class: A, B, and OTHER. *COND_i* is an indicator variable denoting property condition: *ADEQUATE*, *EXCELLENT*, *GOOD*, *NI* (Needs Improvement), *POOR*, and *NA* (Not Available). *MATERIAL_i* is an indicator variable denoting primary construction material: *MASONRY*, *METAL*, *CONCRETE*, *STEEL*, *WOOD*, *NA* (Not Available), Percentages are expressed in decimal form. The sample period spans 1999-2019. N is 30,386 observations.

	Mean	Median	SD	25th Percentile	75th Percentile
Distance Measures					
IXP_DIST	8.354	6.437	7.661	2.633	11.561
IXP < ½ Mile	0.048	0.000	0.214	0.000	0.000
IXP ½ Mile to 1 Mile	0.059	0.000	0.235	0.000	0.000
IXP 1 Mile to 1 ½ Mile	0.049	0.000	0.217	0.000	0.000
IXP 1 ½ Mile to 2 Miles	0.037	0.000	0.190	0.000	0.000
IXP > 2 Miles	0.806	1.000	0.395	1.000	1.000
Property Characteristics					
PRICE ($ millions)	12.700	1.725	51.500	0.849	5.900
LN_PRICE	14.790	14.361	1.456	13.652	15.590
AGE	47.394	38.000	32.080	26.000	62.000
BLDG_SQFT (thousands)	50.981	12.000	130.904	5.346	41.023
LAND_SQFT (thousands)	101.132	29.185	101.664	10.018	87.999
FLOORS	3.330	2.000	5.086	1.000	3.000
CLASS A	0.113	0.000	0.316	0.000	0.000
CLASS B	0.470	0.000	0.499	0.000	1.000
CLASS OTHER	0.417	0.000	0.493	0.000	1.000
COND_ADEQUATE	0.148	0.000	0.355	0.000	0.000
COND_EXCELLENT	0.035	0.000	0.183	0.000	0.000
COND_GOOD	0.106	0.000	0.308	0.000	0.000
COND_NI	0.016	0.000	0.126	0.000	0.000
COND_POOR	0.002	0.000	0.047	0.000	0.000
COND_NA	0.693	1.000	0.461	0.000	1.000
MATERIAL_MASONRY	0.466	0.000	0.499	0.000	1.000
MATERIAL_METAL	0.004	0.000	0.066	0.000	0.000
MATERIAL_CONCRETE	0.116	0.000	0.320	0.000	0.000
MATERIAL_STEEL	0.090	0.000	0.286	0.000	0.000
MATERIAL_WOOD	0.122	0.000	0.328	0.000	0.000
MATERIAL_NA	0.201	0.000	0.401	0.000	0.000

Table 2: Property Value and Distance to IXP

This table presents estimates from hedonic and spatial regressions of price on distance to an internet exchange point (IXP) and property characteristics. *IXP_DIST* is the distance in miles between the property transaction and the location of the IXP. *LN_PRICE* is the natural log of the sale price in USD. *AGE* is the age of the property in years. *BLDG_SQFT* is the total square footage of improvements in thousands of square feet. *LAND_SQFT* is the total square footage of land in thousands of square feet. *FLOORS* is the number of floors in an office property. *CLASS_i* is an indicator variable denoting property class: A, B, and OTHER. *COND_i* is an indicator variable denoting property condition: *ADEQUATE, EXCELLENT, GOOD, NI* (Needs Improvement), *POOR*, and *NA* (Not Available). *MATERIAL_i* is an indicator variable denoting primary construction material: *MASONRY, METAL, CONCRETE, STEEL, WOOD, NA* (Not Available). *LONG* denotes the longitude coordinate of the subject property. *LAT* denotes the latitude coordinate of the subject property. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

	Hedonic Regression	*Spatial Regression*
	LN_PRICE	*LN_PRICE*
IXP_DIST	-0.018***	-0.015***
	(0.000)	(0.000)
AGE	-0.005***	-0.005***
	(0.000)	(0.000)
AGE^2	0.000***	0.000***
	(0.000)	(0.000)
BLDG_SQFT	0.010***	0.010***
	(0.000)	(0.000)
$BLDG\_SQFT^2$	-0.000***	-0.000***
	(0.000)	(0.000)
LAND_SQFT	0.000***	0.000***
	(0.000)	(0.000)
$LAND\_SQFT^2$	-0.000***	-0.000***
	(0.000)	(0.000)
FLOORS	-0.021***	-0.022***
	(0.000)	(0.000)
LONG	0.008	0.009**
	(0.168)	(0.023)
LAT	-0.034	-0.033
	(0.268)	(0.104)
Spatial Dependence	-	0.258***
	-	(0.000)
Spatial Error	-	1.064***
	-	(0.000)
Constant	16.088***	16.084***
	(0.000)	(0.000)
Building Class Dummies	Yes	Yes
Condition Dummies	Yes	Yes
Material Dummies	Yes	Yes
Year Dummies	Yes	Yes
Sub-property type Dummies	Yes	Yes
Sub-market Dummies	Yes	Yes
N	30,368	30,368
R^2(Pseudo R^2)	0.74	0.74

Table 3: Robustness – Controlling for MSA Characteristics, Other Distance Measures, and Local Railway Effects

This table presents coefficient estimates from spatial regressions of price on distance to an internet exchange point (IXP), controlling for property characteristics, MSA characteristics and other distance measures within a MSA, as well as a subsample test focused on MSAs without heavy or light rail transportation systems. *IXP_DIST* is the distance in miles between the property transaction and the location of the internet exchange point (IXP). *HI_POPDENS* is an indicator variable denoting an MSA with a population density above the median value of our sample MSAs. *HI_IXPCOUNT* is an indicator variable denoting an MSA with multiple internet exchange points that is above the median value of our sample MSAs. *GATEWAY* is an indicator variable denoting an MSA that is commonly referred to as a "gateway" city: New York, Boston, San Francisco, Chicago, Los Angeles, and Washington DC. *CBD_DIST* is the distance in miles between the property transaction and the center point of the MSA's central business district (CBD). *MSA_DIST* is the distance in miles between the property transaction and the geographic center point of the MSA. *LINKAGE_DIST* is the distance in miles between the property transaction and the location of the closest airport. *LN_PRICE* is the natural log of the sale price in USD. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Panel A – Controlling for Other MSA Characteristics

	LN_PRICE	*LN_PRICE*	*LN_PRICE*	*LN_PRICE*	*LN_PRICE*	*LN_PRICE*
IXP_DIST	-0.014***	-0.012***	-0.015***	-0.015***	-0.013***	-0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HI_POPDENS	0.625***	0.658***	-	-	-	-
	(0.000)	(0.000)	-	-	-	-
*HI_POPDENS*IXP_DIST*	-	-0.003	-	-	-	-
	-	(0.500)	-	-	-	-
HI_IXPCOUNT	-	-	0.610***	0.564***	-	-
	-	-	(0.000)	(0.000)	-	-
*HI_IXPCOUNT*IXP_DIST*	-	-	-	0.002	-	-
	-	-	-	(0.547)	-	-
GATEWAY	-	-	-	-	0.546***	0.576***
	-	-	-	-	(0.000)	(0.000)
*GATEWAY*IXP_DIST*	-	-	-	-	-	-0.001
	-	-	-	-	-	(0.861)
Spatial Dependence	0.210***	0.194***	0.242***	0.368***	0.273***	0.214***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spatial Error	1.070***	1.072***	1.066***	1.059***	1.062***	1.069***
	(0.002)	(0.005)	(0.000)	(0.000)	(0.000)	(0.002)
Constant	14.800***	14.752***	15.632***	15.352***	16.487***	16.720***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Building Class Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Condition Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Material Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sub-property type Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sub-market Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	30,386	30,386	30,386	30,386	30,386	30,386
Pseudo R^2	0.74	0.74	0.74	0.74	0.74	0.74

Control Variables: AGE, AGE^2, BLDG_SQFT, $BLDG\_SQFT^2$, LAND_SQFT, $LAND\_SQFT^2$, FLOORS, LONG, LAT

Panel B – Controlling for Other Distance Measures and Local Railway Effects

				No Railway Subsample
	LN_PRICE	*LN_PRICE*	*LN_PRICE*	*LN_PRICE*
IXP_DIST	-0.007**	-0.006**	-0.006**	-0.014***
	(0.015)	(0.011)	(0.018)	(0.004)
CBD_DIST	-0.011***	-	-	-
	(0.000)	-	-	-
MSA_DIST	-	-0.010***	-	-
	-	(0.000)	-	-
LINKAGE_DIST	-	-	-0.012***	-
	-	-	(0.000)	-
Spatial Dependence	0.230***	0.234***	0.242***	-0.024**
	(0.000)	(0.000)	(0.000)	(0.015)
Spatial Error	1.068***	1.067***	1.066***	4.361
	(0.001)	(0.001)	(0.000)	(0.377)
Constant	15.845***	15.977***	16.147***	17.424***
	(0.000)	(0.000)	(0.000)	(0.000)
Building Class Dummies	Yes	Yes	Yes	Yes
Condition Dummies	Yes	Yes	Yes	Yes
Material Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Sub-property type Dummies	Yes	Yes	Yes	Yes
Sub-market Dummies	Yes	Yes	Yes	Yes
N	30,386	30,386	30,386	2,406
Pseudo R^2	0.74	0.74	0.74	0.77

Control Variables: AGE, AGE^2, BLDG_SQFT, $BLDG\_SQFT^2$, LAND_SQFT, $LAND\_SQFT^2$, FLOORS, LONG, LAT

Table 4: Further Robustness – Property Value and Establishment of IXP

This table presents coefficient estimates from a multivariate difference-in-difference regression of price on distance from an internet exchange point around the establishment of an IXP (Column 1) and a Heckman two-stage regression examining the impact of distance from an IXP on property value (Column 2 and 3) while controlling for sample selection effects. *IXP < ½ Mile* is an indicator variable denoting whether a property is located less than one-half mile from the location of the internet exchange point (IXP). *AFTER* is an indicator variable equal to one if a property transaction occurred in the year following the establishment of an IXP and zero otherwise. *LN_PRICE* is the natural log of the sale price in USD. *Δ INTERNET_USAGE* is the annual percentage change in the proportion of the state's population that uses the internet. *IXP_EXCHANGE* is a dummy variable equal to one for property transactions that occur after an IXP has been established and zero otherwise. *AGE* is the age of the property in years. *BLDG_SQFT* is the total square footage of improvements in thousands of square feet. *LAND_SQFT* is the total square footage of land in thousands of square feet. *FLOORS* is the number of floors in an office property. *CLASS_i* is an indicator variable denoting property class: A, B, and OTHER. *COND_i* is an indicator variable denoting property condition: *ADEQUATE, EXCELLENT, GOOD, NI* (Needs Improvement), *POOR*, and *NA* (Not Available). *MATERIAL_i* is an indicator variable denoting primary construction material: *MASONRY, METAL, CONCRETE, STEEL, WOOD, NA* (Not Available). *LONG* denotes the longitude coordinate of the subject property. *LAT* denotes the latitude coordinate of the subject property. Results are reported for event horizons measured in years around the date of IXP establishment. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

	Event Study	*Heckman Two-Stage Regressions*	
	[-1,1]	*1st Stage*	*2nd Stage*
	LN_PRICE	*IXP_EXCHANGE*	*LN_PRICE*
IXP < ½ Mile	-0.004	-	0.230***
	(0.961)	-	(0.000)
AFTER	0.056	-	-
	(0.168)	-	-
*IXP < ½ Mile *AFTER*	0.203**	-	-
	(0.039)	-	-
Δ INTERNET_USAGE	-	1.827**	-
	-	(0.016)	-
Constant	39.389*	1.076	16.246***
	(0.066)	(0.730)	(0.000)
Inverse Mills λ	-	-	0.054***
	-	-	(0.004)
Building Class Dummies	Yes	Yes	Yes
Condition Dummies	Yes	Yes	Yes
Material Dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Sub-property type Dummies	Yes	Yes	Yes
Sub-market Dummies	Yes	Yes	Yes
N	4,835	52,078	52,078
R^2 (X^2)	0.79	57789.13	70199.81
Control Variables: AGE, AGE², BLDG_SQFT, BLDG_SQFT², LAND_SQFT, LAND_SQFT², FLOORS, LONG, LAT			

Table 5: Property Value and Distance to IXP – Price-Distance Gradient

This table presents estimates from spatial regressions of price on relative distance to an internet exchange point (IXP) and property characteristics, using dichotomous distance measures. *LN_PRICE* is the natural log of the sale price in USD. *IXP_DIST* is the distance in miles between the property transaction and the location of the internet exchange point (IXP). *IXP < ½ Mile* is an indicator variable denoting whether a property is located less than one-half mile from the location of the internet exchange point (IXP). *IXP ½ Mile to 1 Mile* is an indicator variable denoting whether a property is located between one-half mile and one mile from the location of the internet exchange point (IXP). *IXP 1 Mile to 1 ½ Mile* is an indicator variable denoting whether a property is located between one mile and one and one-half mile from the location of the internet exchange point (IXP). *IXP 1 ½ Mile to 2 Miles* is an indicator variable denoting whether a property is located between one and one-half mile and two miles from the location of the internet exchange point (IXP). *AGE* is the age of the property in years. *BLDG_SQFT* is the total square footage of improvements in thousands of square feet. *LAND_SQFT* is the total square footage of land in thousands of square feet. *FLOORS* is the number of floors in an office property. *CLASS_i* is an indicator variable denoting property class: A, B, and OTHER. *COND_i* is an indicator variable denoting property condition: *ADEQUATE, EXCELLENT, GOOD, NI* (Needs Improvement), *POOR*, and *NA* (Not Available). *MATERIAL_i* is an indicator variable denoting primary construction material: *MASONRY, METAL, CONCRETE, STEEL, WOOD, NA* (Not Available). *LONG* denotes the longitude coordinate of the subject property. *LAT* denotes the latitude coordinate of the subject property. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

	LN_PRICE	*LN_PRICE*
IXP < ½ Mile	0.224***	0.361***
	(0.000)	(0.000)
IXP ½ Mile to 1 Mile	-	0.190***
	-	(0.000)
IXP 1 Mile to 1½ Mile	-	0.142***
	-	(0.000)
IXP 1½ Mile to 2 Miles	-	0.041
	-	(0.140)
Spatial Dependence	0.290***	0.265***
	(0.000)	(0.000)
Spatial Error	1.057***	1.060***
	(0.000)	(0.000)
Constant	16.347***	15.996***
	(0.000)	(0.000)
Building Class Dummies	Yes	Yes
Condition Dummies	Yes	Yes
Material Dummies	Yes	Yes
Year Dummies	Yes	Yes
Sub-property type Dummies	Yes	Yes
Sub-market Dummies	Yes	Yes
N	30,386	30,386
(Pseudo) R^2	0.74	0.74
Control Variables: AGE, AGE^2*, BLDG_SQFT,* $BLDG\_SQFT^2$*, LAND_SQFT,* $LAND\_SQFT^2$*, FLOORS, LONG, LAT*		

Table 6: Descriptive Statistics – Rent Sample

This table presents descriptive statistics for property and lease characteristics of our sample obtained from the CompStak database. *IXP_DIST* is the distance in miles between the property transaction and the location of the internet exchange point (IXP). *IXP < ½ Mile* is an indicator variable equal to one if the distance in miles between the property transaction and the location of the internet exchange point (IXP) is less than ½ Mile, and zero otherwise. *IXP ½ to 1 Mile* is an indicator variable denoting whether a property is located between one-half mile and one mile from the location of the internet exchange point (IXP). *IXP 1 to 1½ Mile* is an indicator variable denoting whether a property is located between one mile and one and one-half mile from the location of the internet exchange point (IXP). *IXP 1½ to 2 Miles* is an indicator variable denoting whether a property is located between one and one-half mile and two miles from the location of the internet exchange point (IXP). *IXP > 2 Miles* is an indicator variable denoting whether a property is located more than two miles from the location of the internet exchange point (IXP). *AGE* is the age of the property in years. *BLDG_SQFT* is the total square footage of improvements in thousands of square feet. *LAND_SQFT* is the total square footage of land in thousands of square feet. *FLOORS* is the number of floors in an office property. *CLASS_i* is an indicator variable denoting property class: A, B, and OTHER. *RENT* is the dollar per square foot annual adjusted effective rent in USD. *LN_RENT* is the natural log of the adjusted effective rent in USD. *SPACE_SQFT* is the amount of space leased by the tenant in thousands of square feet. *TERM* is the number of months until lease expiration. *NEWLEASE* is an indicator variable set equal to one if the lease observation was a new origination. *RENEWAL* is an indicator variable set equal to one if the lease observation is a lease renewal, and zero otherwise. *SUBLEASE* is an indicator variable set equal to one if the lease observation pertains to a sublease agreement, and zero otherwise. *GROSS, TRIPLENET, and NET* are indicator variables denoting the tenant's responsibility for building-level operating expenses. *HIGH_FLOOR, MID_FLOOR,* and *LOW_FLOOR* are indicator variables denoting a lease observation for a unit in the upper third, middle third, or lower third of a building's floors, respectively. *FLOOR _NA* is an indicator variable denoting if the floor number is not available in CompStak's database. *KTI_TENANT* is an indicator variable equal to one if the tenant is in a Knowledge & Technology Intensive (KTI) industry and zero otherwise. Percentages are expressed in decimal form. The sample period spans 1999-2019. N is 83,265 observations.

	Mean	Median	SD	25th Percentile	75th Percentile
Distance Measures					
IXP_DIST	4.720	1.882	7.229	0.593	6.703
IXP < ½ Mile	0.203	0.000	0.402	0.000	0.000
IXP ½ to 1 Mile	0.169	0.000	0.375	0.000	0.000
IXP 1 to 1½ Mile	0.086	0.000	0.281	0.000	0.000
IXP 1½ to 2 Miles	0.050	0.000	0.217	0.000	0.000
IXP > 2 Miles	0.492	0.000	0.500	0.000	1.000
Property Characteristics					
AGE	38.836	32.000	26.030	24.000	44.000
BLDG_SQFT (thousands)	383.201	238.294	426.292	123.880	480.000
LAND_SQFT (thousands)	138.257	73.181	61.425	28.314	192.535
FLOORS	16.513	11.000	15.038	5.000	23.000
CLASS A	0.722	1.000	0.448	0.000	1.000
CLASS B	0.262	0.000	0.440	0.000	1.000
CLASS OTHER	0.016	0.000	0.124	0.000	0.000
Lease Characteristics					
RENT ($ psf)	33.903	29.060	17.652	22.080	40.800
LN_RENT	3.447	3.403	0.450	3.139	3.733
SPACE_SQFT (thousands)	13.156	5.000	33.902	2.453	11.960
TERM (months)	66.361	60.000	37.852	37.000	84.000
NEWLEASE	0.594	1.000	0.490	0.000	1.000
RENEWAL	0.347	0.000	0.476	0.000	1.000
SUBLEASE	0.059	0.000	0.235	0.000	0.000
GROSS	0.816	1.000	0.388	1.000	1.000
TRIPLENET	0.108	0.000	0.310	0.000	0.000
NET	0.076	0.000	0.265	0.000	0.000
HIGH_FLOOR	0.166	0.000	0.372	0.000	0.000
MID_FLOOR	0.201	0.000	0.401	0.000	0.000
LOW_FLOOR	0.186	0.000	0.389	0.000	0.000
FLOOR _NA	0.448	0.000	0.497	0.000	1.000
KTI_TENANT	0.391	0.000	0.488	0.000	1.000

Table 7: Rent and Distance to IXP

This table presents estimates from hedonic regressions of adjusted effective rent on distance to an internet exchange point (IXP), property characteristics, and lease characteristics. *IXP_DIST* is the distance in miles between the property transaction and the location of the internet exchange point (IXP). *IXP < ½ Mile* is an indicator variable equal to one if the distance in miles between the property transaction and the location of the internet exchange point (IXP) is less than ½ Mile, and zero otherwise. *LN_ RENT* is the natural log of the adjusted effective rent in USD. *AGE* is the age of the property in years. *BLDG_SQFT* is the total square footage of improvements in thousands of square feet. *LAND_SQFT* is the total square footage of land in thousands of square feet. *FLOORS* is the number of floors in an office property. *CLASS_i* is an indicator variable denoting property class: A, B, and OTHER. *SPACE_SQFT* is the amount of space leased by the tenant in thousands of square feet. *TERM* is the number of months until lease expiration. *RENEWAL* is an indicator variable set equal to one if the lease observation is a lease renewal, and zero otherwise. *SUBLEASE* is an indicator variable set equal to one if the lease observation pertains to a sublease agreement, and zero otherwise. *TRIPLENET and NET* are indicator variables denoting the tenant's responsibility for building-level operating expenses. *HIGH_FLOOR* and *MID_FLOOR* are indicator variables denoting a lease observation for a unit in the upper third or middle third of a building's floors, respectively. *FLOOR _NA* is an indicator variable denoting if the floor number is not available in CompStak's database. *LONG* and *LAT* are the longitudinal and latitudinal coordinates of the subject property, respectively. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

	LN_RENT	*LN_RENT*	*LN_RENT*
IXP_DIST	-0.004***	-	-
	(0.000)	-	-
IXP < ½ Mile	-	0.009**	0.016***
	-	(0.026)	(0.009)
IXP ½ to 1 Mile	-	-	0.010*
	-	-	(0.063)
IXP 1 to 1 ½ Mile	-	-	-0.007
	-	-	(0.263)
IXP 1 ½ to 2 Miles	-	-	-0.013**
	-	-	(0.045)
Constant	40.387***	41.159***	41.377***
	(0.000)	(0.000)	(0.000)
Building Class Dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Sub-prop type Dummies	Yes	Yes	Yes
Sub-market Dummies	Yes	Yes	Yes
N	83,265	83,265	83,265
R^2	0.69	0.69	0.69
Control Variables: AGE, AGE^2, BLDG_SQFT, $BLDG\_SQFT^2$, LAND_SQFT, $LAND\_SQFT^2$, FLOORS, LONG, LAT, SPACE_SQFT, LEASETERM, RENEWAL, SUBLEASE, TRIPLENET, NET, HIGH_FLOOR, MID_FLOOR, FLOOR _NA			

Table 8: Rent, Distance to IXP, and Knowledge & Technology Intensive (KTI) Tenants

This table presents estimates from hedonic regressions of effective rent on distance to an internet exchange point (IXP), property characteristics, and lease characteristics, conditional on whether the tenant is in a technology intensive industry. *KTI_TENANT* is an indicator variable equal to one if the tenant is in a Knowledge & Technology Intensive (KTI) industry and zero otherwise. *IXP_DIST* is the distance in miles between the property transaction and the location of the internet exchange point (IXP). *IXP < ½ Mile* is an indicator variable equal to one if the distance in miles between the property transaction and the location of the internet exchange point (IXP) is less than ½ Mile, and zero otherwise. *LN_RENT* is the natural log of the dollar per square foot annual adjusted effective rent in USD. *AGE* is the age of the property in years. *BLDG_SQFT* is the total square footage of improvements in thousands of square feet. *LAND_SQFT* is the total square footage of land in thousands of square feet. *FLOORS* is the number of floors in an office property. *CLASS_i* is an indicator variable denoting property class: A, B, and OTHER. *SPACE_SQFT* is the amount of space leased by the tenant in a given lease transaction in thousands of square feet. *LEASETERM* is the number of months until lease expiration. *RENEWAL* is an indicator variable set equal to one if the lease observation is a lease renewal, and zero otherwise. *SUBLEASE* is an indicator variable set equal to one if the lease observation pertains to a sublease agreement, and zero otherwise. *TRIPLENET and NET* are indicator variables denoting the tenant's responsibility for building-level operating expenses. *HIGH_FLOOR* and *MID_FLOOR* are indicator variables denoting a lease observation for a unit in the upper third or middle third of a building's floors, respectively. *FLOOR _NA* is an indicator variable denoting if the floor number is not available in CompStak's database. *LONG* and *LAT* are the longitudinal and latitudinal coordinates of the subject property, respectively. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

	LN_RENT	*LN_RENT*	*LN_RENT*	*LN_RENT*
IXP_DIST	-0.005***	-0.004***	-	-
	(0.000)	(0.000)	-	-
IXP < ½ Mile	-	-	0.009**	0.003
	-	-	(0.027)	(0.464)
KTI_TENANT	0.019***	0.023***	0.019***	0.016***
	(0.000)	(0.000)	(0.000)	(0.000)
*IXP_DIST*KTI_TENANT*	-	-0.001***	-	-
	-	(0.000)	-	-
*IXP < ½ Mile*KTI TENANT*	-	-	-	0.013***
	-	-	-	(0.010)
Constant	40.407***	40.233***	41.185***	41.136***
	(0.000)	(0.000)	(0.000)	(0.000)
Building Class Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Sub-prop type Dummies	Yes	Yes	Yes	Yes
Sub-market Dummies	Yes	Yes	Yes	Yes
N	83,265	83,265	83,265	83,265
R^2	0.69	0.69	0.69	0.69

Control Variables: AGE, AGE^2*, BLDG_SQFT, BLDG_SQFT*^{2}*, LAND_SQFT, LAND_SQFT*^{2}*, FLOORS, LONG, LAT, SPACE_SQFT, LEASETERM, RENEWAL, SUBLEASE, TRIPLENET, NET, HIGH_FLOOR, MID_FLOOR, FLOOR _NA*

Appendix A: Controlling for Other Distance Measures & MSA Characteristics (Lease Data)

This table presents coefficient estimates from hedonic regressions of adjusted effective rent on distance to an internet exchange point (IXP), property characteristics, controlling for other distance measures within an MSA and MSA characteristics. *IXP_DIST* is the distance in miles between the property transaction and the location of the internet exchange point (IXP). *CBD_DIST* is the distance in miles between the property transaction and the center point of the MSA's central business district (CBD). *MSA_DIST* is the distance in miles between the property transaction and the geographic center point of the MSA. *LINKAGE_DIST* is the distance in miles between the property transaction and the location of the closest airport. *HI_POPDENS* is an indicator variable denoting an MSA with a population density above the median value of our sample MSAs. *HI_IXPCOUNT* is an indicator variable denoting an MSA with multiple internet exchange points that is above the median value of our sample MSAs. *GATEWAY* is an indicator variable denoting an MSA that is commonly referred to as a "gateway" city: New York, Boston, San Francisco, Chicago, Los Angeles, and Washington DC. *LN_ RENT* is the natural log of the adjusted effective rent in USD. *AGE* is the age of the property in years. *BLDG_SQFT* is the total square footage of improvements in thousands of square feet. *LAND_SQFT* is the total square footage of land in thousands of square feet. *FLOORS* is the number of floors in an office property. *CLASS_i* is an indicator variable denoting property class: A, B, and OTHER. *SPACE_SQFT* is the amount of space leased by the tenant in a given lease transaction in thousands of square feet. *LEASETERM* is the number of months until lease expiration. *RENEWAL* is an indicator variable set equal to one if the lease observation is a lease renewal, and zero otherwise. *SUBLEASE* is an indicator variable set equal to one if the lease observation pertains to a sublease agreement, and zero otherwise. *TRIPLENET and NET* are indicator variables denoting the tenant's responsibility for building-level operating expenses. *HIGH_FLOOR* and *MID_FLOOR* are indicator variables denoting a lease observation for a unit in the upper third or middle third of a building's floors, respectively. *FLOOR _NA* is an indicator variable denoting if the floor number is not available in CompStak's database. *LONG* denotes the longitude coordinate of the subject property. *LAT* denotes the latitude coordinate of the subject property. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Panel A – Controlling for Other Distance Measures

	LN_RENT	*LN_RENT*	*LN_RENT*
IXP_DIST	-0.002**	-0.003***	-0.003***
	(0.011)	(0.000)	(0.001)
CBD_DIST	-0.003***	-	-
	(0.000)	-	-
MSA_DIST	-	-0.001**	-
	-	(0.011)	-
LINKAGE_DIST	-	-	-0.002**
	-	-	(0.014)
Constant	35.060***	39.226***	40.788***
	(0.000)	(0.000)	(0.000)
Building Class Dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Sub-property type Dummies	Yes	Yes	Yes
Sub-market Dummies	Yes	Yes	Yes
N	83,265	83,265	83,265
Pseudo R^2	0.69	0.69	0.69
Control Variables: AGE, AGE^2, BLDG_SQFT, $BLDG\_SQFT^2$, LAND_SQFT, $LAND\_SQFT^2$, FLOORS, LONG, LAT, SPACE_SQFT, LEASETERM, RENEWAL, SUBLEASE, TRIPLENET, NET, HIGH_FLOOR, MID_FLOOR, FLOOR _NA			

Panel B – Controlling for Other MSA Characteristics

	LN_RENT	*LN_RENT*	*LN_RENT*	*LN_RENT*	*LN_RENT*	*LN_RENT*
IXP_DIST	-0.004***	-0.007***	-0.004***	-0.003***	-0.004***	-0.002*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.100)
HI_POPDENS	12.713***	12.836***	-	-	-	-
	(0.000)	(0.000)	-	-	-	-
*HI_POPDENS*IXP_DIST*	-	0.003**	-	-	-	-
	-	(0.044)	-	-	-	-
HI_IXPCOUNT	-	-	0.700	1.039**	-	-
	-	-	(0.150)	(0.034)	-	-
*HI_IXPCOUNT*IXP_DIST*	-	-	-	-0.011***	-	-
	-	-	-	(0.000)	-	-
GATEWAY	-	-	-	-	12.713***	12.806***
	-	-	-	-	(0.000)	(0.000)
*GATEWAY*IXP_DIST*	-	-	-	-	-	-0.004***
	-	-	-	-	-	(0.004)
Constant	40.387***	40.089***	40.387***	37.803***	40.387***	41.319***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Building Class Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sub-property type Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sub-market Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	83.265	83.265	83.265	83.265	83.265	83.265
Pseudo R^2	0.69	0.69	0.69	0.69	0.69	0.69
Control Variables: AGE, AGE^2, BLDG_SQFT, $BLDG\_SQFT^2$, LAND_SQFT, $LAND\_SQFT^2$, FLOORS, LONG, LAT, SPACE_SQFT, LEASETERM, RENEWAL, SUBLEASE, TRIPLENET, NET, HIGH_FLOOR, MID_FLOOR, FLOOR _NA						

Appendix B: Knowledge & Technology Intensive (KTI) Industry Classifications

This table presents NAICS Industry Category Codes for tenant industries classified as a Knowledge and Technology Intensive (KTI) industry. These codes are used to classify tenants in the CompStak lease database where tenant industry information is available.

NAICS Code	*Industry Category*	*Industry Name*
5112	High Technology (Services)	Software Publishers
5152	High Technology (Services)	Cable and Other Subscription Programming
5161	High Technology (Services)	Internet Publishing and Broadcasting
5179	High Technology (Services)	Other Telecommunications
5181	High Technology (Services)	ISP and Web Search Portals
5182	High Technology (Services)	Data Processing and Related Services
5191	High Technology (Services)	Other Information Services
5413	High Technology (Services)	Architectural and Engineering Services
5415	High Technology (Services)	Computer Systems Design and Related Services
5417	High Technology (Services)	Scientific Research and Development Services
3231	Knowledge Creation	Printing and Related Support Activities
6111	Knowledge Creation	Elementary and Secondary Education
6112	Knowledge Creation	Junior Colleges
6113	Knowledge Creation	Colleges and Universities
6114	Knowledge Creation	Business, Computer and Management Training
6115	Knowledge Creation	Technical and Trade Schools
5191	Knowledge Creation	Libraries and Archives (Other Information Services)
5171	Information Technology	Wired Telecommunications Carriers
5172	Information Technology	Wireless Telecommunications Carriers
5173	Information Technology	Telecommunications Resellers
5174	Information Technology	Satellite Telecommunications
5175	Information Technology	Cable and Other Programming Distribution
5411	Knowledge-Based (Professional Services)	Legal Services
5412	Knowledge-Based (Professional Services)	Accounting Services
5416	Knowledge-Based (Professional Services)	Management and Technical Consulting Services
5418	Knowledge-Based (Professional Services)	Advertising and Related Services
5511	Knowledge-Based (Professional Services)	Management of Companies
5211	Knowledge-Based (Financial Services)	Monetary Authorities
5221	Knowledge-Based (Financial Services)	Depository Credit Intermediation
5222	Knowledge-Based (Financial Services)	Non-depository Credit Intermediation
5223	Knowledge-Based (Financial Services)	Activities Related to Credit Intermediation
5231	Knowledge-Based (Financial Services)	Security and Commodity Investment Activities
5232	Knowledge-Based (Financial Services)	Security and Commodity Exchanges
5239	Knowledge-Based (Financial Services)	Other Financial Investment Activities
5241	Knowledge-Based (Financial Services)	Insurance Carriers
5242	Knowledge-Based (Financial Services)	Agencies and Brokerages and Other Insurance