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Where the Cloud Rests: The Economic Geography of Data Centers

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This study provides an analysis of the entry strategies of third-party data centers in the United States, an industry with assets worth hundreds of billions of dollars. We examine the market in 2018 and 2019, and compare with the physical entry of private data centers for services on demand, including those known as cloud services. We find evidence that providers of third-party data centers trade off the tensions between buyer distaste for distance, which creates localized demand, and costs of supply, which vary with density. We find considerable evidence that localized demand and economies of scale shape entry decisions. We conclude that data centers display tendencies towards urban-biased technical change, and cloud services mildly work to ameliorate such biases. We see little evidence to suggest data centers will spread to any but a small number of low density locations.

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I. Introduction

Did digitization change the strategic role of proximity? Proximity confers competitive advantage through a range of different mechanisms (Alcácer and Chung 2014): Proximity lowers the costs of transportation; enables easier access to skilled labor and innovative complementors; and assists firms in enjoying the shared benefits with others. The increasing digitization of goods and services potentially alters these mechanisms. Digitization lowers the frictions associated with moving information (Goldfarb and Tucker 2019). It enables the creation of services with high "shippability" and such services become deliverable to, and consumable from any connected location (Gervais and Jensen 2019), and it lowers barriers to trading with distant customers with similar tastes (e.g., Blum and Goldfarb 2006, Sinai and Waldfogel 2004). It also enables new strategies for omnichannel retailing (e.g., Brynjolfsson et al. 2009), and fosters the translation of relationships embedded with social trust into online relationships (e.g., Forman et al. 2008).

Data centers are an ideal setting for studying how digitization shapes proximity. The services provided by a data center play an important role in the digital services used and managed by virtually every firm with a large-scale digital presence. On the supply side, data centers display economies of scale, but only after expenditure of extraordinarily large fixed costs for structures that occupy outsized plots of land. If data centers are cost-focused, we would expect them to enter in locations where there is less competition and where the fixed and operational costs associated with the data center facility are low. While they benefit from locating adjacent to pools of network engineers, operating these facilities do not require large numbers of employees, which provides considerable flexibility over their location. This would discourage entry in dense urban areas. On the demand side, the services of data centers travel at the speed of light, which makes them highly shippable and accessible without being geographically proximate. However, buyers for data center services may exhibit a distaste from distance, and have a preference for services from nearby suppliers instead of those who are further away. Such distaste could arise from a mix of factors, which we discuss within the text. If it does matter, it should result in data centers locating in expensive locations near customers and all across the US, with supply and demand determining where and how much. In light of these factors, in this study we ask a counter-intuitive question: Does proximity to local demand shape the entry strategies determining US data centers?

Entry Decisions for Data Centers

At the outset of the commercial internet, virtually every firm housed their servers on company premises. Eventually businesses learned to gain scale economies by consolidating computing resources in another location in a structure known as a data center, communicating with it via the internet. Today virtually every organization in the modern economy employs data centers for essential parts of their electronic commerce and internal digital services. These structures contains many rows of servers on racks, matched to routine operations for support and maintenance. Designers configure these structures to house massive numbers of servers, using architectural features that encourage low-energy use and ensure reliable operations in the event of emergencies, among many features. Today the smallest (largest) data centers house tens (hundreds) of thousands of servers and can cost more than a hundred million (several billion) dollars to construct. The collective value of the assets for this activity exceeds a couple hundred billion dollars in the United States. Regulatory attention, such as those affiliated with the General Data Protection Regulation (GDPR), devotes considerable text to regulating the location of these facilities.

Despite their importance and long history, no research has investigated the entry of data centers. This study is the first to address this gap. We analyze the location of every third-party data center provider in the United States, and supplement that with information about private facilities supporting the cloud market. The analysis tests among different theories of the strategies determining the entry for data center services. Given the novelty of the undertaking, and the lack of knowledge about this core piece of modern information technology, our analysis pursues wide goals. We provide a statistical description of an industry that is not well-understood, and we derive econometric inferences about behavior that had not been scrutinized.

Our analysis treats the location of a facility as an endogenous choice, one that reflects variance in the determinants of demand for a facility at different locations. The inability to directly measure the intensity of distaste for distance frames the principal challenge for this research. Our approach looks for evidence consistent with a model of "distaste for distance." If this factor plays an important role, as hypothesized, then we expect to see its consequences in a variety of choices by suppliers who respond to buyer preferences, and balance those against operational expenses and setup costs, which varies across the US.

The study finds patterns consistent with localization of demand created by distaste for distance. We show that entry follows the features forecast by a threshold model, where all large metropolitan area (with over three quarters of a million people) have at least one local third-party supplier of data services, and only a fraction of small and medium sized urban areas have local suppliers of third-party data services, and no city below a certain size has any data centers (approximately a little more than one hundred and sixty thousand population). In between these two sizes, some areas have entrants and most do not. A high fraction of buyers in small and medium-sized locations must get their services from a non-local supplier (likely located at the closest major city) because little supply locates in their areas.

We also find evidence of heterogeneity in entry strategies from the differences in the behavior of footloose data centers and urban and suburban data centers, where we find different responsiveness to features of local supply and demand. Footloose data centers are more responsive to cost, and that is in spite of evidence about the size of the largest entrants that suggest footloose and urban data centers face the same limiting factors. We also find some similarities between footloose and private cloud providers, though this evidence is imprecisely estimated due to limited number of observations. We also find evidence of the importance of thresholds in the estimates of total demand, where selection based on entry explains much of what we observe.

We estimate a number of threshold models of entry in local markets, and use it to make inferences. We find urban and suburban firms are more prevalent in locations with the type of users who demand these services, and we find evidence that entrants select areas with lower setup costs. For example, local entry rises with the presence of information intensive industries, consistent with the presence of localized demand. We also find evidence that differentiation in the market becomes more prevalent in larger markets, and the findings about the size of the smallest market entrant are consistent with these. If only to reiterate the point, models with more precise demand are better at estimating the cost of supply. Our estimates suggest fixed costs rise and margins decline as we move from the smallest to largest markets, while variable costs do not vary much at all. Yet, entry rises, suggesting a benefit from that location in a major metropolitan area near users.

Contribution

Our research contributes to literature that analyzes the factors that shape the "supply chain" of services that make up the internet, with emphasis on the less visible services that complement internet access, such as storage, distribution, infrastructure security, and names services (Greenstein, 2020). This study answers a call to better understand the impact of ICTs on economic growth (Cardona et al. 2013). While internet access has received considerable attention, only recently have studies begun to examine the uneven supply of the other components that also determine performance. For example, Böttger et al (2016) examines the location of Netflix's CDN network. As one of the largest sources of streaming content in the world, this CDN network is comprised of 4600+ servers in 233 locations in 2016. This is one of many examples of CDNs owned and operated by application firms. Google, Facebook, Apple, Amazon, and Microsoft are all known to support large CDN networks. Nobody has performed a comparable exercise on data centers.

Our research is the first to illustrate the demand for data center services, and, as such, adds to recent research has begun to analyze the impact of cloud providers (Byrne and Corrado 2017, Coyle and Nguyen 2018, DeStefano et al. 2019). Like cloud services, data centers enable flexible and inexpensive uses of storage and computation, remove frictions in access to big data applications, and reduce frictions to supporting applications for a mobile labor force (DeStefano et al. 2019, Jin and McElheran 2019). We differ in focusing on the reasons why providers of services made the decision to enter a local market, wherease prior research takes that entry for granted, and has focused on the consequences of cloud for users.

Because cloud services use data centers so intensively to deliver their service, we relate directly to recent evidence that users of cloud services place high value on physical facilities in closer locations (Wang et al. 2019). Similar to the approach of our study, Wang et al cannot directly view the intensity of demand for local services, but they can infer its presence indirectly from other observable behaviors. Also like this study, estimating a model provides insight into the tradeoffs faced by providers when allocating physical capital to support such services.

Our contribution broadly also contributes to research about the ecosystems supporting usage of advanced IT. As with prior studies, we document a pervasive urban-bias in information technology (Forman et al, 2018). Urban bias arises due to existing concentration of information-intensive activities within urban centers, and due to the private incentive to spread fixed costs by locating near users. Marshallian agglomeration reinforces those incentives, as more data centers enter businesses to locate nearby and vice-versa. Until this point, most of the evidence for the urban-bias of IT comes from studies of broadband (DeStefano, Kneller, and Timmis, 2018, Pew 2019, FCC 2020), business applications (Ceccagnoli et al. 2012, Forman et al. 2009), and markets for technical talent (Tambe 2014). Prior research also focuses on the ability of firms to substitute third-party vendors in a region for internal providers of internet technology (Forman et al, 2008), on the capacity of a region to innovate in a variety of areas, including advanced IT (Delgado, 2012). We are the first to extend that theme to other parts of internet infrastructure, such as data centers. The study also adds an interesting wrinkle to the literature on general purpose technologies, where the entry of data centers is broadly interpreted as a specialty supplier of upstream services in the sense discussed in Bresnahan and Gambardella (1997). They offer analysis of the factors that should encourage entry, such as aggregation from many smaller potential buyers.

While policy-focused research on internet supply chains and local ecosystems describes the many symptoms of the internet's growth and spread around the globe (OECD 2107), statistical studies of infrastructure have neglected data centers and their role in the modern internet. Despite the size of the market and value of the assets, data centers receive little attention in policy reports. This is surprising since these facilities play a key role in virtually all modern internet architectures, and regulatory pressures, such as those affiliated with the General Data Protection Regulation (GDPR), for example, devotes considerable text to regulating the location for storage of data and performance of computation (Zhuo et al. 2020). At a broad level, we contribute to understanding the trade-offs affiliated with unregulated supply and demand, and begin to offer methods for quantifying the trade-offs entrants face without encountering regulatory constraints.

II. Determinants for the location of data centers

Here we describe standard industry practices that affect the supply and demand for data centers. It also informs the statistical analysis.

Costs of Supplying Data Centers

There is substantial sharing of information inside professional associations in North America, and many builders of data centers have national footprints. Hence, we expect a similar set of factors to shape the costs of supplying data centers all across the US.

A new data center takes approximately a year to build, with long time horizons for enormous projects and specialized design elements. The set-up costs include: construction labor and management; the land on which the facility sits; the first generation of equipment and the wiring/racks to support it; building out connectivity to fast backbone internet lines and to (multiple) electrical lines; and tax subsidies and abatements on these initial costs. Special features may be required by users with specific needs, and raise the costs of building. These can include features such as: additional reinforcements to flooring to silence vibrations; raised floors to prevent flooding during hurricanes; extra back-up generators to guarantee reliability in the event of a power outages or weather-related disaster; special cooling to achieve user specifications; and/or multiple lines to support connectivity to multiple networks in the event that one goes down. Construction costs vary widely across locations, and depend on the price of land, labor, permits, property taxes, sales taxes, rebates, and highly specific features of particular plots of land.

At the time of this study, 2018, in many locations the construction costs of a comparatively small data center – some might say minimal, such as 5MW – exceed a hundred million dollars (CBRE, 2015).[2]

[2] Industry convention designated a data center's size by its use of electricity. That leaves the capacity measure flexible enough to handle different uses for the servers, such as storage, computation, and so on.

These costs reach their lowest levels in rural or suburban settings with inexpensive land in warehousing districts, low property taxes, and propitious locations near electrical and data lines. These costs reach their highest levels in dense urban locations, such as Manhattan and San Francisco, and exceed three hundred million dollars. The largest data centers far exceed these sizes, and costs several billion to build from scratch, even in the least expensive locations.

The costs of operating a data center include the costs of electricity for computing equipment and air conditioning equipment[3]; variable cooling and heating requirements, which depend on local weather; local and state economic development incentives, such as tax abatements for sales tax and property taxes; and the costs of gaining additional supply of computing equipment. All these costs rise with capacity, and, thus, qualify as variable costs, distinct from the fixed costs to build from scratch. Operational costs are highest in extremely hot and humid regions, and lowest in moderately cool (northern and not too mountainous) regions with ready access to large volumes of inexpensive electricity (typically hydro-electric). The operational costs of a comparatively small data center can exceed tens of millions of dollars a year, and vary by at least several million year between locations. The operational costs of a large data center can exceed hundreds of millions of dollars per year.

There is an open question about the practical limits on the scale of production. Space to house equipment and the availability of (costly) land in a dense urban area are potential limiting factors on expansion of the size of existing facilities, as are the capacity of electrical supply and data lines to support the operations of the center. Sometimes the requirement for multiple sources of electricity (from different parts of the grid) and multiple lines for data (from different carriers) also places limits on the size and location of a data center. We expect the desire to increase capacity in such a situation, if necessary, will be met with another facility in the same or different location.

Origins of Distaste for Distance

[3] A rule of thumb in the industry estimates the costs of electricity equally split for air conditioning in a moderate climate, and servers in an eight megawatt data center, which would typically house just under fifty thousand servers.

One buyer motivation to use a nearby supplier comes from demand for lower latency, which the user experiences as faster response time. There is intense demand for lower latency among financial users, for example. A related component comes from users seeking to avoid congestion on lines that connect users to data centers, which, again, users experience as faster response in the absence of congestion. This latter motivation arises among "big data" data applications that move terabytes or more of data between storage and computation facilities and user work-places.

Another source of distaste for distance comes from a phenomenon industry participants label as "server hugging" – i.e., executives want to be near the physical facility to manage the physical assets dedicated to supplying their needs. Some of this behavior reflects a desire to monitor shared facilities so a firm receives promised efficiencies (e.g., to adopt cooling or wiring or server design). Some of it reflects the desire to have the option to visit the facility in the event of an urgent situation, even when that might be a low probability (e.g., a hurricane). Some of it may arise from a desire to visit a facility and ensure physical separation of equipment (e.g., keep it safe from theft). Some of it may merely reflect quirky human behavior, and remain hard to rationalize as calculating.

A set of users have demands have the opposite effect. Some users may have little or no desire to ever step foot on the facility. This is typical of generic computing needs, such as backup storage, for example, where best practices counsel buyers to proactively pursue physical separation that lowers risks. Users let others manage the facility and rent space within a data center, and may or may not own the servers that occupy the space. We label such demand as demand for "footloose supply," i.e., demand for supply that comes from anywhere within North America, because it supports users who do not anticipate setting foot on the physical premises of the facility.

Full ownership represents another extreme. For example, some large firms today own and manage their own centers for their company's purposes. Most visibly, firms with large and technically challenging computing needs, such as Facebook, Apple, Microsoft, Amazon, and Google/Alphabet, own all facets of their data centers, and configure the hardware and software to their purposes. Some of these same firms – Microsoft, Amazon, and Alphabet – use their facilities to offer cloud services to users on a rental basis, and gives users the ability to turn the service off and on at will.

III. Data about Data Centers

Our data, collected in February 2018 and February 2019, provides a cross-sectional overview of the market-based supply of facilitiies. First, we collect information on facilities that rent space or equipment for third-party companies to host their data needs. We collect this dataset by scraping data from Baxtel.com and Datacenters.com, two of the largest information resource sites for data centers.[4] We supplement it with information about the facilities of the four largest cloud providers, which are among the worst kept secrets on the internet. Finally, we supplement our rich data on data centers with census data about U.S. counties. This provides information on 1386 data centers in the third-party market. Adding the private centers, we get 1,433 datacenters that are active in February 2019.

Using the physical address of each facility, we identify the county and the Core-based statistical area (CBSA) in which a colocation center locates. We choose to focus on county-level data, rather than more fine-grain data on ICT entry (e.g., Skiti 2020) because we are interested in identifying heterogeneity across markets throughout the country. We show a map of all data centers in the US. As Figure 1 illustrates, data centers are present in every major US region. The map also illustrates that data centers do not concentrate their locations exclusively in locations with the lowest costs.

INSERT FIGURE 1

Data Centers Location

[4] Our data sources (Baxtel.com and Datacenters.com) are two known sources of information on third-party data centers. Datacenters.com is the largest marketplace for colocation data center services (in transaction volume and revenue).

We locate data centers in counties. Tables 1a and 1b shows that almost all data centers reside in counties that are part of a Metropolitan Statistical Areas (MSAs), namely, large urban and suburban areas with medium to large populations. Over 96.4% of counties with at least one *third-party* data center are MSAs (Table 1a).[5] The census classifies 37.2% of US counties as MSAs, so Table 1 shows that a small number of data centers locate in low density counties. More than 2000 US rural and micropolitan[6] counties have no provider. We next find a smaller percentage of *private* data centers locate in urban area – i.e., 73% of counties with at least one *private* data center are MSAs (Table 1b).

Table 2a introduces variables to operationalize the types of data center entry that we observe in a county. A county can have *Urban*, *Suburban*, *Footloose*, or *Private* supply of data centers. The first three are defined by their distance from the nearest downtown area containing concentrations of business, who are the principal buyers of services from data centers. Within each MSA, we identify the downtown hubs in order to estimate the largest clusters of economic activity within the nearby area. Each MSA contains at least one downtown hub, although some MSAs that have up to three. For example, the San Jose-Sunnyvale-Santa Clara MSA was assigned three downtown hubs; one for each city named in the MSA. We geocode the longitude and latitude of each downtown and data center, and calculate the distance between each data center and its nearest downtown area. In experiments not shown here we implemented numerous slights variations on this definition, and found it made no qualitative difference.[7] Table 2a shows that 1171 data centers are either urban or suburban, again, hinting that, even by the simplest measure, most data centers locate near a set of users within cities.

In Table 2b, we provide basic descriptive statistics about capacity. While the industry measures the capacity of a data center by its electrical usage, we do not have access to such information. Instead, our main measure of capacity, termed *Gross SQFT*, is a continuous variable that measures the total data center capacity (in square ft.) that is operating in the county. About a quarter of our sample reports this directly, so, instead,

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[5] The first calculation is the # of counties in MSAs over the total # of counties (1,173/3,150). The second is to calculate the # of counties in MSAs with at least one data center against all counties with at least one data center (218/26).

[6] Micropolitan areas have less than 50k population.

[7] In the analysis in the text, we define urban as data centers within 5 km of a downtown, footloose as those outside of 30km, and suburban and those between 5 and 30km.

we construct a measure we can use on the entire sample. We estimate the total square footage of the facility based on images of each data center facility from Google Maps. The vast majority of data centers are one story buildings, so square footage corresponds with total capacity.[8] The table shows an interesting trend in the capacity of data centers of each type. Footloose and private data centers are 25% to 30% larger in square footage on average than urban and suburban data centers, consistent with the importance of land costs as a determinant of location.

Table 2b provides clues about the replacement value of these assets covered by third-party providers and private suppliers.[9] It takes a simple calculation to show that it must be on the order of magnitude in the hundreds of billions of dollars. Here is a brief review of the reasoning: A data center of *minimal* (5MGW) size is typically less than 100k square feet. As Table 2b shows, most of these data centers are larger than the minimal size. Such small data center costs over $100 million to build in a low cost suburban location and over $300 million to build in the expensive urban locations. The most common estimate is $250 million for many cities over a million population (CBRE, 2015). Using those to benchmark an approximation, the value of the assets easily reaches a couple hundred billion.[10] Reiterating, we do not offer that as a precise estimate of asset value, but, rather, as an estimate of the order of magnitude, which – with any estimate – must add up to a sum in the hundreds of billions.

Our main measure of entry, termed *Data Center County*, is a dummy variable for whether there was at least one data center operating in the county. For the ordered logit specification, we construct a categorical variable, *Data Center Count*, categorized by whether there are 0, 1, 2, 3, or more than 3 data centers. Table 2c

[8] The rare exception are retrofitted buildings, such as the converted RRDonnelly building 350 E. Cermak in Chicago, which contains 1.1 million square feet, and is the largest third-party data center in North America. Other exceptions are data centers fit into a dense urban settings with extremely expensive land, such as Manhattan or San Francisco, and in these cases we can obtain total square footage. About 25% of the data centers in our sample provide details about the total square footage. We validated that our square footage estimates are consistent with these available statistics.

[9] Replacement value is standard concept for asset valuation. It values an asset at the cost of reconstruction from scratch.

[10] For a conservative estimate, value the footloose and private data centers (average size: 450k sq ft and $465 sq ft) at $500m, value the suburban data centers at (average size: 375k sq ft) at $400m, and value the urban data centers (average size: 345k sq ft) at $800m. There are 103 urban, 149 suburban, 47 footloose, and 26 private data centers. Hence, a conservative estimate is 103*800 + 149*400 + 47*500 + 26*500 = $183.5 billion. The order of magnitude is "a couple hundred billion," as stated in the text.

provides the distribution of these situations, showing entry for the 218 counties with any entry (i.e., less than 18.6% of MSAs). Only 76 counties have only one, 34 have two, 23 have three, 17 have four, and 68 have five or more. In other words, most counties that have a data center contain few entrants, while the vast majority of data centers locate in MSAs with 5 or more entrants.[11]

INSERT TABLES 1 AND 2

Given the prevalence of data centers in MSAs, we choose to focus our statistical analysis on counties that are located within an MSA, where we will be able to estimate the thresholds of entry. It is not possible to make statistical inferences about areas other than MSAs. As a practical matter, this restriction to MSAs has no consequences for the estimation because adding addition low density counties would not alter that estimate of the threshold for determining entry.

Descriptive Patterns of Data Centers and Population

Before performing econometric estimation, we show the correlational patterns between population and data center entry/capacity. These correlations give an indication about what the statistical estimates will show about the role of thresholds determined by market size. Figure 2 shows a scatter plot between the number of data center entrants and the logged population of each county. There is a positive correlation between population and the number of data centers in a county, consistent with the hypothesis that entry grows with larger local demand. The correlation is not high, only 0.42. That is because entry behavior is discontinuous. There is also no entry of third-party data centers below a population level corresponding to approximately 160,000 people. All locations with areas above approximately 700,000 people have at least one entrant. If an area between those two population levels experiences entry, it tends to be the more populous county.

[11] Santa Clara County (aka Silicon Valley) has the largest number, with 71. Followed by Los Angeles County, CA, Dallas County, TX, Cook County, IL, New York County, NY, Maricopa County, AZ, Fulton County, GA, Harris County, TX, Middlesex County, MA, Miami-Dade County, FL, and Loudoun County, VA (with 21).

Interestingly, however, population alone does not predict entry for the cities with the largest population. The variance is quite large, with some experiencing many entrants and some not.

Evidence about capacity partly helps to resolve the puzzle. Figure 3 shows the relationship between logged population and logged capacity of data centers, which is the sum of the square footage of all data center facilities in each county. The figure includes only counties with at least one data center, and drops all counties with none. We categorize each county by the type of data center that has the largest share of capacity. For example, if a county has 200,000 SQFT of urban data centers and 50,000 SQFT of footloose data centers, we categorize that county as an urban county.

INSERT FIGURES 2 AND 3

Consistent with localized demand, capacity and population are positive correlated –i.e., 0.596 without private data centers. We also find, interestingly, that capacity is not synonymous with number of entrants, especially for the largest areas. We speculate that suppliers adjust their capacity to demand, either with new additions to existing building or new buildings altogether. Relatedly, we also speculate that growth over time by suppliers -- either adjusting entry or expanding capacity – has some consequences for what we observe, and that will generate challenges for inference.

The county with the largest capacity, Loudon, VA, ranks as the county with the tenth largest number of entrants. That location was home to MAE-East, one of the earliest data-exchange points on the commercial internet, and today contains a number of Amazon's data centers. As it turns out, the firms who locate in Loudon operate some of the very largest data centers in the US.[12] While it contains features consistent with self-reinforcing agglomeration economies, we do not observe those features at any other location, and so, we hesitate to draw a conclusion that agglomeration effects operate widely. Just as likely, the capacity in Loudan may reflect demand among users in Washington, D.C. and Baltimore and the surrounding MSA, which is one

[12] Footloose firms largely inhabit Loudoun, VA. It is followed by Dallas, TX, Santa Clara, CA, Cook, IL, Los Angeles, CA, Maricopa, AZ, Middlesex, NJ, Harris, TX, King, WA, NY, NY, and Fulton, GA.

of the largest concentrations of data-intensive work in the US, along with other potential demand for footloose supply (e.g., from Amazon Web Services) from the users in the mid-Atlantic region more broadly.

We next examine the smallest entrant in each location. If localization of demand shapes entry, then a subtle test involves a comparison of **the size of the smallest entrant in each location.** An entrant must cover their fixed costs. If prices rise in high cost areas, then it is possible for the minimal viable entrant to be smaller. This would arise, for example, with differentiated specialist services in urban areas. A related question is whether differentiated entrants are prevalent in only larger markets.

Figure 4 shows the relationship between the logged population and the logged value of the smallest data center in each market. When we exclude the private data centers, smaller entrants are more viable in counties with higher populations. The correlation is -0.533 without the private data centers. Notice that the pattern is discontinuous. Below half a million population, there is no visible relationship. The small entrants increase only after the populations exceed at least half a million. The distribution also shifts downward in locations over one million in population. The smallest data centers in locations exceeding a million exceeds the smallest entrant in locations under half a million.

INSERT FIGURE 4

This pattern suggests that entrants in urban areas may benefit from the local demand for specialized services and receive higher margins compared to private data centers that rely on economies of scale. As a measure of the prevalence of specialist entry, we also computed the frequency of qualification to handle specialized needs from buyers within financial or medical services. For medical services, we look for adoption of HIPAA (Health Insurance Portability and Accountability Act of 1996) and HITECH (Health Information Technology for Economic and Clinical Health Act of 2009) standards. For financial data, we look for adoption of the SOC 1 and SOC 2 standards.[13] In Table 3, we find that third-party vendors that offer specialized services

[13] Source: https://www.ssae-16.com/soc-1/

are more prevalent on average in major markets compared to minor markets. There are 3.776 specialists on average in major markets, while there are only 1.048 specialists on average in minor markets.[14] In addition, while more than 75% of major markets provide at least one data center that has adopted a specialized standard, only 43% of minor counties have at least one specialist data center. From these results, we infer that models of undifferentiated entry are plausible for markets with small population levels.

INSERT TABLE 3

Another interesting statistic compares the capacity of the largest suppliers. The s**ize of the largest viable entrant** reflects factors that constrain the size of a data center, and provide a test of the limits of economies of scale. The size of local demand may limit the size of a data center, as could the cost of land. We compare the largest data centers in rural locations, and infer whether many factors limit the size of urban data centers. If urban data centers are larger than any data centers in rural locations, then no limitation shapes urban data center size. If rural data centers are larger, then data centers escaping the limitations of urban locations achieve new levels of economies of scale.

Figure 5 shows the relationship between logged population and the logged largest data center in a location. Excluding the private data centers, the figure shows a pattern of rising maximum capacity with population levels, as expected, though there is considerable variance around that correlation. The correlation is 0.574 without the private data centers. Also notable, there also are similar maximum capacities between private (in rural counties) and large third-party data centers (in urban and suburban settings), which suggests that there are limits to the economies of scale, and available land is largely not the limiting factor for private data centers. However, the size of the largest private data center exceeds the size of about half the largest third-party data centers in a number of areas with population over a million population, suggesting that *some* of the private data centers could be constrained.

[14] A major market has population above 750,000. We find similar results across different threshold definitions.

INSERT FIGURE 5

IV. Statistical Testing for Localization

Did distaste for distance create the patterns observed in figures 2-5? If it plays a significant role, it will create localized demand for services in distinct geographic markets, where each firm supplies services to local business customers. A simple model can guide statistical analysis, and can provide inference about the importance of different types of cost in firm entry decisions (e.g., Xiao and Orazem 2011).

Model

We use a variant of Bresnahan and Reiss' (1991) to identify determinants of entry. The main endogenous variable depends on whether a data center enters a region or not. There are three categories of determinants, respectively, F, M, and N, for fixed costs of serving the market, variable profits per customer served, and total number of customers. Profits for a data center are M*N – F. A firm decides to be present when it is profitable, i.e., when $M*N \geq F$. Regional factors determine the level of M, N and F. Further index different each region by i, where i represents a county. Each location contains a population of potential customers, Pop_i, and two types of shifters, one for mark-ups, which are a function of the type of demand, X_{Di}, and one for variable costs, X_{Ci}. In other words, the function M describes the relationship between average revenue per customer (e.g., presence of big data users) and variable cost per customer (e.g., local electrical prices).

First consider entry into an area, and the profits of a firm who has a monopoly on the market. Designate the variable profit per customer as $M^1(X_{Di}, X_{Ci})$, and the number of customers for the firm as $N^1(Pop_i)$. The function N^1 describes the relationship between Pop_i, and the number customers served. Profits for a single entrant are: $M^1(X_{Di}, X_{Ci}) * N^1(Pop_i) - F_i$.[15]

[15] A few standard normalizations ease exposition. We assume $N^1(0) = 0$, and that, within the relevant range, more of X_{Di} raises demand, and, therefore, variable profits per customer, i.e., $dM^1/dX_{Di} > 0$, and $M^1(0, dX_{Ci}) = 0$. When the cost shifter, dX_{Ci}, rise, then variable profits per customer decline, i.e., $dM^1/dX_{Ci} < 0$.Though less essential, we also assume

The key property of this model is its **threshold, which determines the number of entrants.** For any given X_{Di}, there is an Pop^*_i, such that $M^1(X_{Di})*N^1(Pop_i) > F$ for any $Pop_i \geq Pop^*_i$. There is no entry for $Pop_i < Pop^*_i$. For any level of profit per customer, entry is not profitable without enough customers. Similarly, for a level of customers, entry is not profitable without customers that demand services with high margins.[16] The related intuition also holds: If customers and margins grow as we compare locations, then, ceteris paribus, at some point demand must be sufficiently large to support at least one entrant. A related threshold property holds for variable costs.[17] If costs are sufficiently low, there must be at least one entrant, but above some level it will not be in any firm's interest to enter.[18]

How about a second entrant in this model? Following the approach in Bresnahan and Reiss, we can posit a second set of functions with two symmetric entrants as $M^2(X_{Di}, X_{Ci})$, and the number of customers for each firm as $N^2(Pop_i)$. Profits for each firm is $M^2(X_{Di}, X_{Ci})*N^2(Pop_i) - F_i$, where profits are split between them. The results follow the same logic as above. For any level of variable profit per user, it takes a sufficient population to make it profitable to enter, and that exceeds the level necessary to support the first entrant. For any population level, it takes more demand and lower costs under duopoly to make it profitable to enter, again, exceeding what it took to induce the first entrant.[19] This simple logic easily extends to the third and fourth entrant.

Entry responds to variation in fixed costs. Yet, it is also too simple to say that lower fixed costs leads to more entrants. Rather, as fixed costs decline, threshold population levels decrease, threshold demand

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there exists a sufficiently large X'_{Ci}, such that $M^1(X_{Di}, X'_{Ci}) = 0$, i.e., a sufficiently high cost reduces average profits per customer to zero or less.

[16] There is an X^*_{Di}, such that $M^1(X_{Di})*N^1(Pop_i) > F$ for all $X_{Di} > X^*_{Di}$,, and no entry for $X_{Di} > X^*_{Di}$.

[17] There must be an X^*_{Ci}, such that for all X_{Ci}, $< X^*_{Ci}$.

[18] Formally, the model yields an implication about how the threshold changes as fixed costs change, $dPop^*_i/dF > 0$ and $dX^*_{Di}/dF > 0$. The threshold population and demand required to support an entrant rises when fixed costs are larger. Similarly, $dX^*_{Ci}/dF < 0$. The threshold level of cost to support an entrant declines when fixed costs are higher.

[19] Note that this too yields a set of thresholds for Pop^{**}_i, X^{**}_{Di}, and X^{**}_{Ci} under similar conditions as those that governed M^1 and N^1. How do the two sets of thresholds stand in relation to each other? First, we assume $M^1(X_{Di}, X_{Ci}) > M^2(X_{Di}, X_{Ci})$ for any level of X_{Di} and X_{Ci} in the relevant range of these variables. That is, for a given level of demand two competitors leads to lowers markups from the level reached with one. Second, like above, $N^2(0) = 0$ and $M^2(0, dX_{Ci}) = 0$. Third, $dM^1/dX_{Di} > dM^2/dX_{Di}$ and $dM^1/dX_{Ci} < dM^2/dX_{Ci}$. It also follows that $X^{**}_{Di} > X^*_{Di}$, and $X^{**}_{Ci} < X^*_{Ci}$.

shifters decrease, and threshold variable costs increase. Eventually a reduction in fixed costs can lead to more entry, but the entry occurs as a non-convex and discontinuous event.

Estimation

The model leads to an approach for estimation. We observe an entrant when $M^*N \geq F$, which can be expressed as $\ln(M) + \ln(N) \geq \ln(F)$. Adding an error term, we can estimate a logit or probit, where features of local markets are designated as X. If $M = C(X_{Ci})U(X_{Di})$, $\ln(M) = K_{CD} + X_{Ci}B_C + X_{Di}B_D$, where the first term estimates the level of marginal costs, and the second one estimates the percentage markup over costs per unit of marginal cost. Further let $\mathrm{Ln}(N) = K_{Pop} + B_{Pop}X_{Pop}$, and $\ln(F) = K_F + B_FX_F$, where these are potential customers and fixed costs. Altogether, it becomes a threshold model in which $Y = K_{CD} + X_{Ci}B_C + X_{Di}B_D + K_{Pop} + B_{Pop}X_{Pop} + K_F + B_FX_F$, where B_F, B_{Pop}, B_D, and B_C act as weights to be estimated in a logit or probit model. All the constants – i.e., K_{CD} K_{Pop} K_F – add up to one constant in estimation, so average differences in in fixed or variable costs and average margins are not identified.

Measuring Determinants of Entry

We seek to test whether localized demand generates behavior consistent with threshold models. The Bresnahan and Reiss model identifies shapers of demand from presuming that more entry occurs when local areas have features consistent with high demand, and low variable and fixed cost. With only industry beliefs and no prior analysis, we opt to err on the side of including many variables (without introducing multicollinearity). Table 4 summarizes the definitions of variables.

Some variables track local demand for data centers. First, we use the 2012 economic census to observe the level of employment, by county, for two-digit NAICS codes. We focus our analysis on a set of industries that are most IT-intensive: Information, Healthcare, Manufacturing, Education and Finance & Real Estate. We operationalize each sector's economic activity by calculating the percentage of employees in a county employed in that industry. We use data from the Esri 2016 demographics dataset to obtain zip code-level and county-level measures. We examine the mean level of education within a county by examining the percentage of the population with at least a bachelor's degree.

It is unclear whether population or population density best inform us about potential customers because these are highly correlated, and both are correlated with the prevalence of unobservable types of demanders. Multicollinearity precludes including both. After experimentation, we concluded it was better to include population density, measured by the population per square mile. That aligns well with measuring heterogeneity in population density within a county by creating measures for the lowest and highest population density areas by zip code.[20]

A set of variables tests among different determinants of the operating costs of running a data center in a location. First, we collect data from the EIA to obtain 2016 state-level average electricity prices to industrial customers to create a measure of *Industrial Electric Price*.[21] Second, we collect data on Daily Air Temperatures from 2016 and 2016, by county, from the CDC Wonder North America Land Data Assimilation System. We examine how weather shapes operating costs by creating a measure of the average temperature during *Hot* months and *Cold* months in each county.

We next examine labor costs for maintaining each facility. We collect data from the BLS about the median hourly wage of network engineers in each county in 2016. For other digital technologies, such as software, the availability of IT talent is associated with entry patterns (Bennett and Hall 2020). Finally, we obtain data about MSA-level real estate tax (RET) rate in 2010 from the Tax Foundation.[22] We operationalize this measure by creating indicators for whether a county is located in an MSA in the top quartile of sales tax, *High Sales Tax*, or located in a MSA in the bottom quartile of sales tax*, Low Sales Tax*.

A set of variables tests among different determinants of set-ups costs. First, we approximate land costs by collecting county-level data on the median home value by square foot from Zillow.[23] To account for heterogeneity in land costs within a county, we create measures for the lowest and highest median home value

[20] Population and density are highly correlated in this data.
[21] We also used the prices to commercial customers that is also provided by the EIA. Our results do not change when we use alternative measures.
[22] https://taxfoundation.org/major-metropolitan-area-sales-tax-rates/

[23] https://www.zillow.com/research/data/

areas by zip code. Second, we obtain data about state-level real estate tax (RET) rates by collecting data from the National Association of Home Builders.[24] We operationalize this measure by creating indicators for whether a county is located in a state in the top quartile of RET, *High Real Estate Tax*, or located in a state in the bottom quartile of RET, *Low Real Estate Tax*.

We next examine how labor costs vary for facilities in different locations. To operationalize this, we collect data from the BLS about the median hourly wage of construction laborers in each county in 2016.[25] Finally, we examine how local government incentives in the form of tax abatements can relieve the costs associated with building a data center. Using data from the CBRE on tax incentives for the 30 largest enterprise markets, we construct an indicator, *Tax Break MSA*, to measure whether a county is based in a MSA that provided tax breaks to data centers in 2015.[26]

INSERT TABLE 4

Table 5 shows summary statistics. As noted earlier, only 18.6% of counties have at least one data center. When we examine the types of data centers, we observe several interesting patterns. On average, there is more suburban capacity than any other type of capacity, followed by urban and then footloose capacity. The amount of suburban capacity in a county is almost three times higher than the footloose capacity (47,622 SQFT vs. 17,869 SQFT). We also observe that our capacity measurements appear to have a skewed distribution. Similarly, we observe that our density variables appear to have a skewed distribution. We apply a log-transformation for both exogenous and endogenous variables in our analysis.

INSERT TABLE 5

[24] http://www.nahbclassic.org/generic.aspx?genericContentID=250239&fromGSA=1
[25] For counties that did not provide an estimate of the hourly wage of network engineers or construction laborers, we used averages from each MSA or each state.
[26] Compiled from CBRE Research, "Site Selection Strategies for Enterprise Data Centers," https://www.cbre.com/research-and-reports/Site-Selection-Strategies-for-Enterprise-Data-Centers, December 2015, accessed January 2020.

V. Estimation

Table 6 present the estimates on the entry of *any* data centers. All estimates focus on the threshold between zero and one. In column 1, we use an OLS model to predict entry. In column 2, we use a logit model as an alternative specification, the endogenous variable is an indictor variable.

First, for our demand variables, we find that some demand factors lead to more entry. The proportion of Information and FIRE (Finance, Insurance, and Real Estate) employees statistically predicts entry. A one standard deviation increase in the supply of Information workers is associated with a 2.7% increase in the likelihood of data center entry into a county; similarly, a standard deviation increase in the proportion of FIRE workers is associated with a 4.2% increase in the likelihood of entry into a county. None of the other types of users matter, including manufacturing or health workers.

Having a population density one standard deviation above the mean level is associated with a 13.3% increase in the likelihood of entry into a county. There is a negative association between the size of the minimum population density in a county and the likelihood of entry. The latter result is consistent with the interpretation that data centers locate in the places within a county with the lowest density (e.g., parcel of large available land). These results are consistent with localized demand.

Second, for our cost variables, we find that an increase in median home values is associated with an increase in the likelihood of entry. This goes in the opposite direction of predictions, and likely reflects unobserved demand correlated with high value homes. However, consistent with the finding about minimum density, we find that for land value, entry decreases as the minimum land value increases. Most of the other estimates for variable and fixed costs are not statistically significant.

Overall, this model of the margin between none and one entrant generates weak results. We conclude that more refinements are required to make robust inferences.

INSERT TABLE 6

Heterogeneity of Effects across Data Centers

Local demand should not shape the decision of footloose suppliers, who, by assumption, satisfy national demand, and, hence, locate in response to localized costs but not local demand. If that case, X_{Di} should determine the decisions of local suppliers, but those same factors should not determine entry of footloose suppliers. A similar statement holds for private data centers for the provision of cloud service. Once again, if we reject this pattern in the data, then the strong assumptions or misclassification may be held responsible. If we cannot reject, then it is one piece of evidence consistent with expectations about localization of competition.

In Table 7, we examine entry thresholds for different types of data centers. First, we find that while urban and suburban data center entry is sensitive to *L. population density* and percentage *FIRE*, footloose data center entry is not impacted by these demand measures. A one standard deviation increase in *L. population density* above the mean is associated with a 9.28% increase in the likelihood of urban data center entry into a county and 16.7% increase in the likelihood of suburban data center entry into a county. Increasing the proportion of FIRE labor by one standard deviation above the mean is associated with a 1.7% increase in the likelihood of urban data center entry and a 2.6% increase in the likelihood of suburban data center entry. These estimates go in the predicted direction, and their differences with footloose also are consistent with the role of localized demand.

When we look at our costs variables, we find that footloose data centers are more sensitive to the cost of land and cold weather. A one standard deviation increase in the average temperature during cold months above the mean is associated with a 2.8% change in the likelihood of footloose data center entry. Land values matter for footloose entry. Increasing the Median Home Value per SQFT by one standard deviation above the mean is associated with a 1.6% change in the likelihood of footloose data center entry. Perhaps the most surprising finding is for electricity, which has no effect on the marginal entrant. Finally, we find that the private and footloose firms are similar, but since the sets of estimates for private data centers is comparatively weak, these are not surprising findings.

We test between models using the log ratio test. We do not find evidence to reject the hypothesis of equality between the urban and suburban models. We perform a similar test for footloose and private, and do not find enough to distinguish between the models. However, we do find that there are differences between the footloose and urban models. Thus, while the entry behavior of urban and suburban data centers are similar, they differ from footloose. This is consistent with localized demand varying in importance for different types of providers.

INSERT TABLE 7

More Precise Cost Estimates

Our ability to measure distaste for distance and competitive pressures are indirect. To gain more precise estimates, we adopt a flexible functional form for demand, and use it to generate precision in the estimates for cost estimates. This approach simultaneously estimates of a threshold for the marginal entrant at zero/one, one/two, two/three, three/four, four/five or more. For this exercise we do not distinguish between urban, suburban, or footloose data centers. In other words, this model assume the same function for demand and costs in every location, but different demand functions across the margins between no entry, monopoly, duopoly, triopoly, quadopoly and more.

More formally, we adopt a flexible function for margins within the function ln(M). That translates into a different margin function for monopoly, duopoly, triopoly, and quadopoly. Thus, $\ln^1(M) = K^1_{CD} + X_{Ci}B_C + X_{Di}\, B^1_D$, $\ln^2(M) = K^2_{CD} + X_{Ci}B_C + X_{Di}\, B^2_D$, $\ln^3(M) = K^3_{CD} + X_{Ci}B_C + X_{Di}\, B^3_D$, and so on. Relatedly, and given our concerns about unobservable features of demand correlated with population, we also do not place restrictions on the estimates for $K_{Pop} + B_{Pop}X_{Pop}$, and include a different estimate for each threshold. Once again, the constants will not be identified. Finally, we estimate these together in maximum likelihood, which assumes a shared error distribution. That makes $B^1{}_D$ and $B^2{}_D$ and $B^3{}_D$ comparable up to a scalar.

Table 8a contains the estimates. The estimates for variable and fixed costs are in one column, while the estimates for margins are in four columns. The first column provides the estimate for the threshold between none and one entrant, referred to here as the function for monopoly margins. The next columns provide the estimate of the difference between the monopoly margin and duopoly, triopoly and quadopoly margin function. We perform log ratio tests to jointly test each margin. We do not find enough evidence to distinguish between monopoly and duopoly, and we find enough to distinguish between the thresholds for monopoly and triopoly, and thresholds between monopoly and quadopoly. Overall, we do not reject the model, but the model is not precise at every threshold.[27]

The coefficient estimates for markups for any entry are comparable in sign to previous findings for the threshold that determines the difference between zero and a monopoly entrant. As with prior estimates, larger information industries and FIRE encourages the margins that encourage entry, as do population density, as well as a smaller minimum population density. A percentage point increase in the share of Information workers is associated with a 11.8% increase in the margins for a potential entrant and a percentage point increase in the share of FIRE workers is associated with a 10.8% increase in the margins for a potential entrant. A one percent change in population density is associated with a .393% increase in the margins for the first entrant, while a one percentage increase in the minimum population density is associated with a .124% decrease in the margins of the first entrant. A new finding are the importance of health – more discourages margins for the first entrant, and maximum density – more encourages margins. A percentage point increase in the supply of Healthcare workers is associated with a 3.9% decrease in the margins for the first entrant, while a one percent increase in the maximum density is associated with a .282% increase in the margins of the first entrant.

[27] We only show results for the most flexible model, and do not show the models with incremental differences. Log ratio tests clearly accepted different constants for the threshold between monopoly, duopoly, triopoly and quadopoly, while the tests for adding more nuanced flexibility, as shown, were weaker, as discussed in the text.

Compare those estimates across different thresholds. The monopoly and duopoly margins have no statistical significance (consistent with the log ratio test comparing these two). The results differ between monopoly and triopoly, with the presence of health no longer playing a role,[28] and the role of density also no longer playing a role[29] (though min and max continue to do so). For quadopoly, the percent of population with a bachelor's degree plays a positive role, unlike in monopoly. Health and density no longer plays a role, however.[30] Most puzzling, information technology plays a discouraging role in going from the third to the entry with four or more entrants.[31]

The benefit of this specification appears in the estimates for costs. The estimates for variable cost align with prior findings, though with more statistical precision than we have seen in any previous table. The estimates for network engineer wage are negative, the estimates for cold are positive, and the estimates for hot are negative. A one dollar increase in the hourly network engineer wage leads is associated with a 3.5 percent decrease in margins. A one degree change in cold temperatures is associated with 2.6 percent increase in margins for entrants. A one degree increase in temperature during the peak hot season is associated with a 4 percent decrease in the margins of entrants. Once again, to our surprise, real estate taxes and electrical prices do not obtain statistical significance.

The estimates for fixed costs find a positive significant estimate on areas that have tax abatement programs (i.e., tax break), and high sales taxes. Being located in a MSA that support data center tax breaks is associated with a 48.5% increase in margins. Being located in a county in the top quartile of sales tax is associated with a 26.5% increase in margins. More expensive home values discourages entry by raising costs, while a high minimum home value discourages entry. A dollar increase in the median home value per SQFT is associated with a 0.2% increase in margins, while a dollar decrease in the minimum ZIP-level home value per SQFT is

[28] The key estimates add up to an estimate than is not different from zero. That is, the estimates for health add up to statistical zero, or -0.039 + 0.065 = 0.026.
[29] The estimates for density add up to statistical zero, or 0.393 - 0.210 = 0.183.
[30] In the case of the health, health adds up to statistical zero, or -0.039 + 0.093 = 0.054, and density adds up to statistical zero, or 0.393 – 0.216 = 0.177.
[31] In this case, 0.118 – 0.471 = -0.353.

associated with a 1% increase in margins. Once again, construction wages seem to play no role, nor do low sales taxes.

Table 8b shows the implications for margins, variable costs and fixed costs. We take all firms in monopoly, and compute the estimated variable and fixed costs and margins without a constant. Next, we compute the mean and median for this group of firms. We do the same for firms in duopoly, triopoly, and quadopoly. We perform a similar simulation of cost for the data centers in the top ten most popular locations. Since everything is in logs, the difference between numbers is informative about the percentage difference attributable to observable factors, or how much a firm's margins and costs would change if it moved to another areas.

The table shows the implied variable costs are generally the same for firms in each market, but the fixed costs rise as we move from smaller to bigger markets. The margins move around among monopoly, duopoly, triopoly and quadopoly, and the large markets having the lowest margins. The top areas with the most entry have the highest fixed costs and the lowest margins. Taken a face value, the estimates say the margins are 48% lower[32] and the fixed costs are 24% higher.[33] Since there are little or no perceptible change in variable cost, and a measurable increase in the estimated constant, these estimates can only be reconciled in a few ways. There must be (a) an effiency gain that lower costs that raises returns for all entrants in the big market but cannot be measured (and end up in the unidentified constant)[34], and/or (b) the variable profits in the top markets are not nearly as high as they are in the uncompetitive markets. We do not have enough information to choose among these possibilities, but we do see entry reaching high levels in the top market, suggesting (a) is more likely, i.e., locating in a major metropolitan area, and near users, makes up for these more challenging cost conditions and more competitive margins.

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[32] In this case, 4.834 – 4.349 = 0.485.

[33] In this case, 0.151 + 0.093 = 0.244.

[34] Any general benefit gained by all entrants in top markets will end up in the unidentified constant. That goes for either from less volutal demand or higher reliability in infrastructure or any other unmeasurable effect.

INSERT TABLES 8a and 8b

Capacity

Estimating demand requires a two equation approach, where the first equation accounts for selection by threshold into a situation in which positive entry occurs. The second equation predicts total demand, conditional on entry. Entry and demand for capacity are sensitive to different margins. According to the above model, for example, X_{Di} and X_{Ci} should play a role in determining total quantity demanded, while X_{Fi} should not affect demand for capacity on the margin.

In Table 9, we show the estimates for demand, as measured by capacity. Total capacity in an areas measures quantity demanded under the assumption that mismeasurement in demand – i.e., the difference between measured capacity and the actual quantity demanded -- arises randomly across locations. We perform a Heckman correction to predict capacity after conditioning on entry.

The demand-side effects for the information and FIRE industries do not predict demand, once we control for selection of any entry. We do find that population density is associated with a positive and significant increase for Urban and Suburban capacity. A 1% increase in population density is associated with a 1.059% increase in urban capacity, and a 1.416% increase in suburban capacity.

We find little evidence that footloose capacity responds to lower variable costs except in one area. As expected, lower industrial electric prices are associated with higher footloose capacity. A one dollar unit increase in industrial electric prices is associated with a 31.3% decrease in footloose capacity. No other localized capacity is responsive to electricity prices. We also find that colder locations have high capacity for footloose suppliers, again, as expected. A one degree difference in temperature during the peak winter season is associated with a 10.4% change in footloose capacity.

Overall, only a few coefficients predict capacity, once we control for entry, so only weak conclusions emerge. Though we see some differences across the coefficients for local and footloose equations, the differences are not dramatic except for electricity. We conclude that entry behavior is more informative about local demand and supply than quantity demanded as measured by capacity.

INSERT TABLE 9

Alternative Definitions of Data Center Geography

We perform several additional tests to test our definition of footloose, suburban, and urban data centers. We find that our results are robust even when we designate that urban data centers are all data centers within 10 Kilometers of an MSA downtown area and when we designate that suburban data centers include all data centers between 10 KM and 40 KM of an MSA downtown area. In addition, we proxy the density of the zip code of each data center to test whether it is located in a central (e.g. urban) area in the county. Again, our results are robust to this definition of data center type. Finally, we test whether aggregating our data to the MSA-level changes our results. Given that our definition of data center type is based at the MSA-level, it seems fair to test our demand and cost shifters at this level of analysis. We find even sharper support for our results when we test at this level.

VI. Managerial Implications

Our findings are consistent with a role for localized demand as an explanation for variance in entry strategy. We find that a threshold model provides a useful lens for understanding entry. All large metropolitan area (with over three quarters of a million people) have at least one local third-party supplier of data services, and only a fraction of small and medium sized urban areas have local suppliers of third-party data services, and no city below a certain size has any data centers (approximately a little more than one hundred and sixty thousand population). In between these two sizes, some areas have entrants and most do not. A high fraction of small and medium-sized locations must get their services from a non-local supplier (likely located at the closest major city).

Our approach overcomes the inability to measure the intensity of distaste for distance. We measure the influence of localized demand indirectly, by measuring the determinants of the entry of data centers throughout the country. We find patterns consistent with tension between economies of scale and localized demand across US cities.

We analyze a range of statistical evidence. We find urban and suburban firms are more prevalent in locations with the type of users who demand their services, and we find evidence that entrants select areas with lower costs. For example, local entry rises with the presence of information intensive industries, consistent with the presence of localized demand. We also find evidence that differentiation in the market becomes more prevalent in larger markets, and the findings about the size of the smallest entrant are consistent with these.

We also find differences in the behavior of footloose and urban and suburban data centers, where we see distinctly different responsiveness to features of local demand. Footloose data centers are also more responsive to cost, and that is in spite of evidence about the size of the largest entrants that suggest footloose and urban data centers face the same limiting factors. We also find some similarities between footloose and private cloud providers.

We estimate a Bresnahan and Reiss model with flexible demand structure, which yields better estimates of the cost of supply. Taken a face value, the estimates say the margins are 48% lower in a top market in comparison to a monopoly market due to observable factors, and that the fixed costs are 24% higher due to observable factors. We infer it is likely that all urban providers get a benefit that makes up for the higher setup costs and lower margins. The local demand considerations has a more central role than supply considerations in the entry decisions of data center firms.

Overall, the evidence suggests data centers and cloud services have an urban bias, favoring bigger and denser cities. There is scant evidence that data centers will spread to non-urban locations. At most, our finding suggest such activities will come from few private data centers, and perhaps a few footloose data centers searching for low electricity prices. Even as demand spreads to the cloud, more likely, the infrastructure to support it will locate in suburban areas with low costs, and sufficiently close to potential customers in order to relieve concerns about network congestion.

This research speaks to two distinct views that animate open questions about digital infrastructure supply. An outlook that could be labeled as "optimistic" anticipates experimentation in a few places, followed by more diffusion to more users, more regions, and a larger set of applications. It interprets the state of digital infrastructure at a point in time as temporary and transient, and in the midst of wider diffusion. In contrast, an outlook that might be labeled as "pessimistic" stresses that digital infrastructure has achieved higher productivity in dense locations. That arises due to economies of scale in equipment, due to increased productivity from the colocation of many related activities, and due to the availability of skilled labor in urban areas in developed economies. Overall, the experience with data centers supports the less optimistic view, due to the concentration of supply around urban cities, and the persistent demand for local supply.

This study offers three main managerial implications. First, this study quantifies how data center managers trade-off between the setup and operational costs of running a facility and capturing local demand. While supplier proximity to users who demand data center services alleviate a buyer's "distaste for distance", these markets are also associated with higher setup costs and lower margins.

This study also offers evidence that data center managers who provide specialized services display an urban bias. When there is enough local demand from potential buyers, this provides more opportunity to provide differentiated services within a data center.

Finally, we expect that managers who operate businesss in small and medium cities will be most affected by the geographic choices of vendors. They either must build for their own use, and not gains the benefits of scale economies from sharing infrastructure with others unless they get supply from distant locations, and give up the benefits of close proximity. Deeper research can address some of the tension. For example, though managers prefer a local supply of infrastructure when it is available, it may be possible to use remote data centers or cloud storage to manage the potential latency issues associated with congestion on data lines and to cater to specialized needs.

References

Alcácer J, Chung W (2014) Location Strategies for Agglomeration Economies. *Strateg. Manag. J.* 35(12):1749–1761.

Bennett VM, Hall TA (2020) Software Availability and Entry. *Strateg. Manag. J.* 41(5):950–962.

Blum BS, Goldfarb A (2006) Does the Internet Defy the Law of Gravity? *J. Int. Econ.* 70(2):384–405.

Böttger T, Cuadrado F, Tyson G, Castro I, Uhlig S (2016) Open Connect Everywhere: A Glimpse at the Internet Ecosystem through the Lens of the Netflix CDN. *CoRR*.

Bresnahan TF, Gambardella A (1997) The Division of Labor and the Extent of the Market. *Work. Pap.*:1–34.

Bresnahan TF, Reiss PC (1991) Entry and Competition in Concentrated Markets. *J. Polit. Econ.* 99(5):977–1009.

Brynjolfsson E, Hu Y, Rahman MS (2009) Battle of the Retail Channels: How Product Selection and Geography Drive Cross-Channel Competition. *Manage. Sci.* 55(11):1755–65.

Byrne D, Corrado C (2017) ICT Services and their Prices: What do they tell us about Productivity and Technology? *Financ. Econ. Discuss. Ser.*:1–43.

Cardona M, Kretschmer T, Strobel T (2013) ICT and Productivity: Conclusions from the Empirical Literature. *Inf. Econ. Policy2* 25(3):109–125.

Ceccagnoli M, Forman C, Huang P, Wu DJ (2012) Co-creation of Value in a Platform Ecosystem: The Case of Enterprise Software. *MIS Q.* 36(1):263–290.

Coyle D, Nguyen D (2018) Cloud Computing and National Accounting. *ESCoE Discuss. Pap. 2018-19* (December):1–59.

DeStefano T, Kneller R, Timmis J (2018) Broadband infrastructure, ICT Use and Firm Performance: Evidence for UK firms. *J. Econ. Behav. Organ.* 155:110–139.

DeStefano T, Kneller R, Timmis J (2019) Cloud Computing and Firm Growth. *Nottingham Cent. Res. GEP 20/02*.

Forman C, Ghose A, Goldfarb A (2009) Competition between Local and Electronic Markets: How the Benefit of Buying Online Depends on Where You Live. *Manage. Sci.* 55(1):47–57.

Forman C, Ghose A, Wiesenfeld B (2008) Examining the Relationship between Reviews and Sales: the Role of Reviewer Identity Disclosure in Electronic Markets. *Inf. Syst. Res.* 19(3):291–313.

Gervais A, Jensen JB (2019) The Tradability of Services: Geographic Concentration and Trade Costs. *J. Int. Econ.* 118:331–350.

Goldfarb A, Tucker C (2019) Digital Economics. *J. Econ. Lit.* 57(1):3–43.

Jin W, McElheran K (2019) Economies Before Scale: Survival and Performance of Young Plants in the Age of Cloud Computing. *SSRN Work. Pap.*:1–77.

Sinai T, Waldfogel J (2004) Geography and the Internet: Is the Internet a Substitute or a Complement for Cities? *J. Urban Econ.* 56(1):1–24.

Skiti T (2020) Strategic Technology Adoption and Entry Deterrence in Broadband. *Ind. Corp. Chang.* 29(3):713–729.

Tambe P (2014) Big Data Investment, Skills, and Firm Value. *Manage. Sci.* 60(6):1452–1469.

Wang S, LaRiviere J, Kannan A (2019) Spatial Competition and Missing Data: An Application to Cloud Computing. *Work. Pap.*:1–23.

Xiao M, Orazem PF (2011) Does the Fourth Entrant Make any Difference?: Entry and Competition in the Early U.S. Broadband Market. *Int. J. Ind. Organ.* 29(5):547–561.

Zhuo R, Huffaker B, kc claffy, Greenstein S (2020) The Impact of the General Data Protection Regulation on Internet Interconnection. *NBER Work. Pap.* No. 26481.

Table 1a: Sample Construction for Third-Party Data Centers. This table shows the number of counties with at least one third-party data center across Metropolitan Statistical Areas (MSA), Micropolitan Statistical Areas (mSA), and rural areas (None).

	Counties	Counties with Data Center(s)	% Counties with Data Center(s)
MSA	1,173	218	18.70%
mSA	641	6	0.94%
None	1,336	2	0.15%

Table 1b: Sample Construction for Private Data Centers

	Counties	Counties with Data Center(s)	% Counties with Data Center(s)
MSA	1,173	19	1.62%
mSA	641	5	0.78%
None	1,336	2	0.15%

Table 2a: Classification of Endogenous Variables. We assigned a data center to one of four mutually exclusive categories based on the usage and distance of each data center to the closest downtown hub.

Data Center Type	Definition	Count
Urban	Any Data Center within 5 km of a MSA's downtown hub.	564
Suburban	Any Data Center between 5 km and 30 km of a MSA's downtown hub.	627
Footloose	Any Data Center more than 30 km away from a MSA's downtown hub.	185
Private	Data Center that is owned and used exclusively by a single organization.[35]	57
Total # of DCs		1,433

Table 2b: Endogenous Variables Descriptives

Type	Counties with DCs of type	Mean # of DCs of type / County	Mean Capacity of type/ County
All Counties	1,173	1.18	106,966
Data Center Counties	218	6.33	545,528
Urban	103	4.21	345,888
Suburban	149	3.70	374,904
Footloose	47	4.02	455,672
Private	26	2.19	465,492

Table 2c: Distribution of number of entrants

# of DCs in County	**# of Counties**	**Total number of DCs**
0	955	0
1	76	76
2	34	68
3	23	69
4	17	68
5 or more	68	1152

[35] We examined cloud data centers owned and used by the following companies: Microsoft, Google, Facebook, and Amazon.

Table 3: **Specialization analysis**. The table shows the mean number of datacenters within a county that are compliant with various standards and the proportion of counties with at least one specialist data center. HIPAA and HITECH are relevant to organizations that handle personal health information in any capacity. SOC 1 and SOC 2 are a set of standards relevant to demonstrate that an organization has the appropriate controls in place to protect and account for financial data. A major market is defined as a county with a population greater than 750,000.

	Major Market				Minor Market			
	HIPAA	HITECH	SOC 1	SOC 2	HIPAA	HITECH	SOC 1	SOC 2
Mean Data Centers	3.684	0.776	1.605	2.184	1.048	0.267	0.381	0.571
Counties with Specialist (%)	76.32	39.47	51.32	61.84	42.86	17.14	19.05	26.67

Table 4: Definition of Demand & Supply Variables.

Variable	Definition
% Information	% of county's employees in Information sector (NAICS: 51).
% Health	% of county's employees in Health sector (NAICS: 62).
% Education	% of county's employees in Education sector (NAICS: 61).
% FIRE	% of county's employees in FIRE (Finance, Insurance, Real Estate) sectors (NAICS: 52-53).
% Manuf.	% of county's employees in Manufacturing sector (NAICS: 32-33).
Pop. Density	Population Density (pop./square mile).
Min. Density	Lowest Population Density Zipcode in a county
Max. Density	Highest Population Density Zipcode in a county
Industrial Electric Price	State-level average price of electricity to industrial customers (cents/kilowatt-hour) in 2016.
Tax break MSA	County in MSA that gave out tax breaks to data centers (source: CBRE).
Median Home Val (per SQFT)	Estimated median home value/ SQFT in a county.
Min. Home Value (per SQFT)	minimum home value/SQFT zipcode in a county.
Max. Home Value (per SQFT)	maximum home value/SQFT zipcode in a county.
Low Real Estate Tax	Indicator for a county that has a RET (state-level) in the bottom quartile.
High Real Estate Tax	Indicator for a county that has a RET (state-level) in the top quartile.
Low Sales Tax	Indicator for a county that is an MSA with a 2016 Sales tax rate in the bottom quartile.
High Sales Tax	Indicator for a county that is an MSA with a 2016 Sales tax rate in the top quartile.
Cold	Avg. Temperature during 3-month period of December 2015, January, February 2016.
Hot	Avg. Temperature during 3-month period of June, July, August 2016.
Median Network Engineer Wage	2016 Median hourly wage of network engineers in the county.
Median Construction Wage	2016 Median hourly wage of construction laborers in the county.
Median Age	Median age in the county.
% Bachelors Degree	% of population with at least a bachelor's degree.

Table 5: Summary Statistics of Demand & Supply Variables.

	mean	s.d.	min	max
Dependent Variables				
Data Center County	0.186	0.389	0	1
Urban DC County	0.088	0.283	0	1
Suburban DC County	0.127	0.333	0	1
Footloose DC County	0.039	0.194	0	1
Private DC County	0.022	0.147	0	1
Gross Capacity	106966.300	561541.200	0	9782365
Urban Capacity	30372.060	233390.900	0	3534329
Suburban Capacity	47622.020	279482.200	0	5583060
Footloose Capacity	17869.480	226941.400	0	6149277
Demand Shifters				
% Bachelor's Degree	17.371	7.108	4.854	55.464
% Information	1.085	1.193	0	15.066
% Health	10.126	4.373	0	44.326
% Education	0.210	0.253	0	3.008
% FIRE	3.180	2.198	0	29.758
% Manufacturing	8.241	6.489	0	40.011
Population Density	644.237	2912.159	0.8	72158
Min. Density	23.057	163.762	0	2793.67
Max. Density	4342.058	10916.470	0.814	172373.4
Variable Cost Shifters				
Industrial Electric Price	6.978	2.011	4.66	22.92
Low Real Estate Tax	0.251	0.434	0	1
High Real Estate Tax	0.225	0.418	0	1
Median Network Engineer Wage	30.440	4.466	18.25	46.87
Cold	29.247	8.120	7.163	55.975
Hot	65.710	7.322	38.188	79.25
Fixed Cost Shifters				
Median Construction Wage	14.519	3.982	8.21	29.38
Tax break MSA	0.163	0.369	0	1
Low Sales Tax	0.255	0.436	0	1
High Sales Tax	0.211	0.408	0	1
Median Home Val (per SQFT.)	117.638	74.574	36	590
Min. Median Home Val	84.444	43.580	18	437
Max. Median Home Val	139.142	113.642	24	1142
Counties	1173			

Table 6: Entry Analysis of Data Centers. The dependent variable in the OLS and Logit model is DataCenterCounty, an indicator for whether there was any DC entry in the county. The Logit model show odds-ratios. Our observations include all 1,173 counties that are located in MSAs.

	OLS	Logit
Demand Shifters		
% Bachelor's Degree	0.001	1.024
	(0.002)	(0.026)
% Information	0.044***	1.314**
	(0.010)	(0.136)
% Health	-0.007**	0.940
	(0.002)	(0.033)
% Education	0.008	1.038
	(0.049)	(0.652)
% FIRE	0.033***	1.248***
	(0.005)	(0.069)
% Manufacturing	-0.005**	0.953
	(0.002)	(0.027)
L Pop. Density	0.064***	1.887***
	(0.013)	(0.284)
L Min. Density	-0.028***	0.805*
	(0.008)	(0.069)
L Max. Density	0.016	1.750***
	(0.008)	(0.202)
Variable Cost Shifters		
Industrial Electric Prices	0.005	1.071
	(0.005)	(0.061)
Low Real Estate Tax	-0.015	0.696
	(0.023)	(0.217)
High Real Estate Tax	-0.026	0.738
	(0.025)	(0.208)
Median Network Engineer Wage	-0.002	0.939
	(0.003)	(0.034)
Cold	0.002	1.035
	(0.002)	(0.019)
Hot	-0.003	0.952*
	(0.002)	(0.019)
Fixed Cost Shifters		
Median Construction Wage	0.004	1.046
	(0.003)	(0.040)
Tax break MSA	0.046	2.227*
	(0.028)	(0.719)
Low Sales Tax	-0.038	0.686
	(0.023)	(0.222)
High Sales Tax	0.066**	1.420
	(0.025)	(0.369)
Median Home Value (per SQFT)	0.001**	1.006*
	(0.000)	(0.003)
Min. Home Value (per SQFT)	-0.002***	0.981***
	(0.000)	(0.004)
Max. Home Value (per SQFT)	0.000	1.000
	(0.000)	(0.001)
Constant	-0.126	0.002
	(0.149)	(0.004)
Adjusted R^2	0.3821	-
Observations	1173	1173

Table 7: Entry Analysis of Data Centers by Type. All models are logit and the coefficients are in odds-ratios. The dependent variable is an indicator for the entry of a data center of a particular type (All, Urban, Suburban, Footloose, or Private) in the county.

	(7.1) All	(7.2) Urban	(7.3) Suburban	(7.4) Footloose	(7.5) Private
Demand Shifters					
% Bachelor's Degree	1.024	1.006	1.026	1.126**	0.895*
	(0.026)	(0.034)	(0.026)	(0.047)	(0.045)
% Information	1.314**	1.321*	1.129	1.280	1.860***
	(0.136)	(0.145)	(0.101)	(0.173)	(0.303)
% Health	0.940	0.936	0.901**	1.005	0.958
	(0.033)	(0.045)	(0.036)	(0.068)	(0.067)
% Education	1.038	0.895	3.172*	0.181	0.681
	(0.652)	(0.753)	(1.631)	(0.221)	(0.966)
% FIRE	1.248***	1.169**	1.176**	1.039	1.135
	(0.069)	(0.066)	(0.061)	(0.085)	(0.085)
% Manufacturing	0.953	0.880**	0.976	1.095*	1.02
	(0.027)	(0.043)	(0.029)	(0.050)	(0.042)
L Pop. Density	1.887***	2.104***	2.142***	0.816	1.462
	(0.284)	(0.405)	(0.341)	(0.226)	(0.429)
L Min. Density	0.805*	0.883	0.810*	1.058	0.460*
	(0.069)	(0.091)	(0.070)	(0.128)	(0.147)
L Max. Density	1.750***	2.401***	1.481**	1.833**	0.974
	(0.202)	(0.397)	(0.188)	(0.430)	(0.214)
Variable Cost Shifters					
Industrial Electric Prices	1.071	1.200**	1.071	0.819	0.402*
	(0.061)	(0.084)	(0.064)	(0.089)	(0.155)
Low Real Estate Tax	0.696	1.656	0.818	0.311	0.253
	(0.217)	(0.631)	(0.286)	(0.229)	(0.196)
High Real Estate Tax	0.738	0.872	0.849	3.138*	1.393
	(0.208)	(0.315)	(0.252)	(1.631)	(0.871)
Median Network	0.939	0.843***	0.905**	1.290***	1.142
Engineer Wage	(0.034)	(0.041)	(0.035)	(0.096)	(0.092)
Cold	1.035	1.044	1.000	1.109**	0.946
	(0.019)	(0.025)	(0.021)	(0.035)	(0.047)
Hot	0.952*	0.890***	0.964	0.971	0.959
	(0.019)	(0.024)	(0.022)	(0.033)	(0.038)
Fixed Cost Shifters					
Median	1.046	0.942	1.030	1.008	0.804*
Construction Wage	(0.040)	(0.049)	(0.040)	(0.067)	(0.087)
Tax break MSA	2.227*	1.204	2.255*	2.472	1.552
	(0.719)	(0.532)	(0.743)	(1.189)	(0.941)
Low Sales Tax	0.686	0.556	0.817	0.879	0.755
	(0.222)	(0.270)	(0.283)	(0.543)	(0.49)
High Sales Tax	1.420	1.623	1.474	0.992	0.936
	(0.369)	(0.515)	(0.399)	(0.464)	(0.625)
Median Home Value	1.006*	0.997	1.001	1.008*	1.001
(per SQFT)	(0.003)	(0.004)	(0.003)	(0.003)	(0.007)
Min. Home Value	0.981***	0.979***	0.989*	0.978***	1.018*
(per SQFT)	(0.004)	(0.005)	(0.004)	(0.006)	(0.009)
Max. Home Value	1.000	1.002	1.000	1.000	0.995
(per SQFT)	(0.001)	(0.002)	(0.001)	(0.002)	(0.004)
Observations	1173	1173	1173	1173	1173

Notes: Exponentiated coefficients; Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8a: Flexible Margin Model of entry of Data Centers. This model imposes no restrictions on margins and does same function on variable costs and fixed costs.

	(8.1) First entrant	(8.2) Addition of Second entrant	(8.3) Addition of Third entrant	(8.4) Addition of Fourth entrant
Demand Shifters				
% Bachelor's Degree	0.013	-0.006	0.021	0.040*
	(0.014)	(0.013)	(0.018)	(0.022)
% Information	0.118**	-0.046	-0.137	-0.471**
	(0.060)	(0.049)	(0.095)	(0.139)
% Health	-0.039**	0.024	0.065**	0.093**
	(0.018)	(0.020)	(0.028)	(0.042)
% Education	-0.162	-0.081	-0.294	0.093
	(0.335)	(0.254)	(0.467)	(0.668)
% FIRE	0.108***	-0.012	-0.018	-0.006
	(0.026)	(0.031)	(0.037)	(0.046)
% Manufacturing	-0.029**	-0.020	0.008	0.024
	(0.014)	(0.014)	(0.022)	(0.032)
L Pop. Density	0.393***	-0.089	-0.210*	-0.216*
	(0.081)	(0.073)	(0.112)	(0.135)
L Min. Density	-0.124**	0.018	-0.025	0.0513
	(0.047)	(0.043)	(0.057)	(0.068)
L Max. Density	0.282***	0.017	0.076	-0.080
	(0.061)	(0.076)	(0.116)	(0.151)
Constant	-2.470**	1.030	0.800	2.065*
	(0.954)	(0.652)	(0.924)	(1.094)
Variable Cost Shifters				
Industrial Electric Prices				0.021
				(0.027)
Low Real Estate Tax				-0.183
				(0.157)
High Real Estate Tax				-0.107
				(0.143)
Median Network Engineer Wage				-0.035**
				(0.018)
Cold				0.026**
				(0.010)
Hot				-0.040***
				(0.010)
Fixed Cost Shifters				
Median Construction Wage				0.025
				(0.019)
Tax break MSA				0.485**
				(0.157)
Low Sales Tax				-0.215
				(0.163)
High Sales Tax				0.265**
				(0.130)
Median Home Val (per SQFT)				0.002*
				(0.001)
Min. Home Value (per SQFT)				-0.010***
				(0.002)
Max. Home Value (per SQFT)				0.000
				(0.001)

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8b: **Estimated costs**

	monopoly	duopoly	triopoly	quadopoly	Top Market[36]
Margins					
Mean	4.834	4.615	5.254	4.598	4.349
Median	4.833	4.457	5.374	4.643	4.360
Fixed Cost					
Mean	-0.093	-0.001	0.0297	0.131	0.151
Median	-0.058	-0.033	-0.036	0.155	0.211
Variable Cost					
Mean	-2.804	-2.843	-2.783	-2.850	-2.872
Median	-2.846	-2.900	-2.861	-2.946	-3.030

[36] We define the ten largest counties (by population) as a top market.

Table 9: Heckman Analysis of Data Centers. The second stage estimates capacity across different types of data centers using demand and variable cost regressors. The first stage in the Appendix estimates entry (of any type) with the full set of demand, fixed cost, and variable cost regressors.

Second Stage	L Total SQFT	L Urban SQFT	L Suburban SQFT	L Footloose SQFT
Demand Shifters				
% Bachelor's Degree	-0.045	-0.133	-0.015	0.165*
	(0.025)	(0.079)	(0.081)	(0.067)
% Information	0.206*	0.669*	-0.079	0.242
	(0.088)	(0.273)	(0.281)	(0.234)
% Health	-0.102**	-0.185	-0.388**	0.117
	(0.037)	(0.117)	(0.120)	(0.098)
% Education	0.419	-3.162	8.283***	-5.234**
	(0.698)	(2.209)	(2.269)	(1.868)
% FIRE	0.078	0.198	0.156	-0.287*
	(0.053)	(0.167)	(0.172)	(0.142)
% Manufacturing	0.018	-0.146	0.089	0.247**
	(0.032)	(0.105)	(0.108)	(0.087)
L Pop. Density	0.426**	1.059*	1.416**	-1.309**
	(0.160)	(0.505)	(0.518)	(0.427)
L Min. Density	-0.132	-0.233	-0.375	0.344
	(0.075)	(0.233)	(0.239)	(0.200)
L Max. Density	-0.346*	1.763***	-0.807	-0.047
	(0.159)	(0.507)	(0.520)	(0.426)
Variable Cost Shifters				
Industrial Electric Prices	-0.040	0.163	0.039	-0.313*
	(0.048)	(0.149)	(0.153)	(0.127)
Low Real Estate Tax	0.126	1.148	0.173	-0.689
	(0.305)	(0.965)	(0.991)	(0.817)
High Real Estate Tax	0.527*	-0.533	0.515	2.222**
	(0.265)	(0.838)	(0.861)	(0.710)
Median Network	0.057	-0.508***	-0.225*	0.625***
Engineer Wage	(0.034)	(0.109)	(0.112)	(0.092)
Cold	0.008	0.061	-0.082	0.104*
	(0.015)	(0.048)	(0.049)	(0.041)
Hot	-0.024	-0.149**	0.019	0.043
	(0.018)	(0.058)	(0.059)	(0.049)
Constant	12.643***	10.869	12.004	-16.373**
	(2.166)	(7.032)	(7.181)	(5.875)
lambda	-0.997**	0.129	-0.364	-2.246*
	(0.369)	(1.169)	(1.200)	(0.987)
Observations	1173	1173	1173	1173

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$

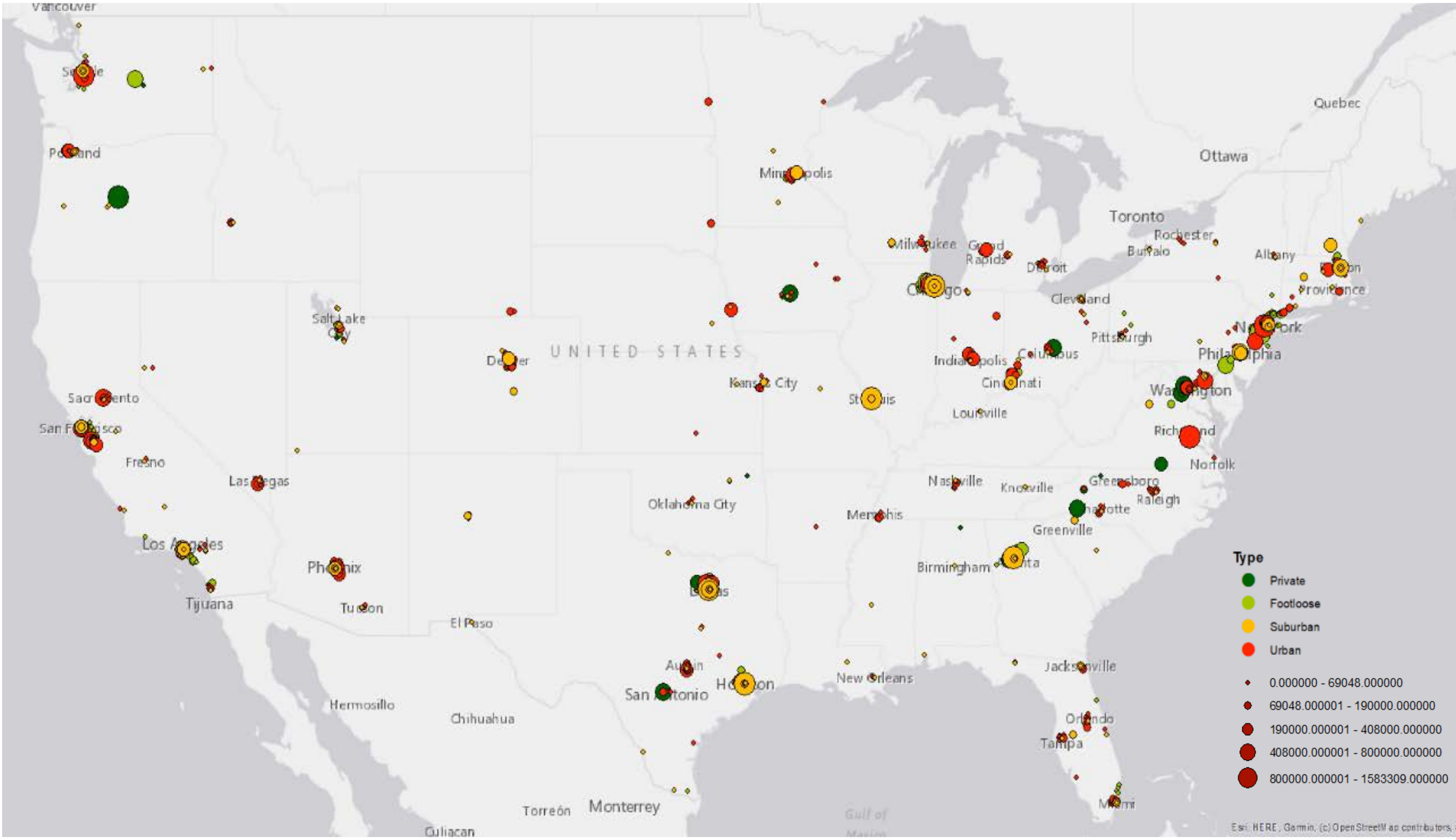

Figure 1: Geography of Data Centers. This figure maps out the geographic locations of data centers. Each point represents a data center, and is color-coded by type and weighted by the total capacity of the facility (in SQFT).

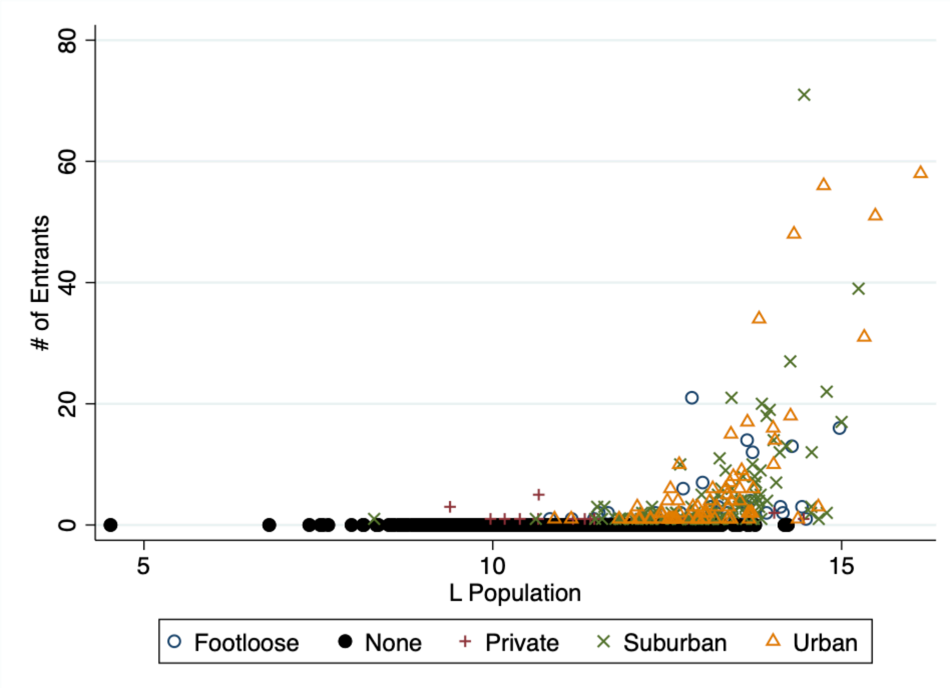

Figure 2: Population vs Entry. This graph demonstrates the relationship between county population and the number of data center entrants within the county. A county is assigned a type based on what type of data center has the largest share of capacity within the county.

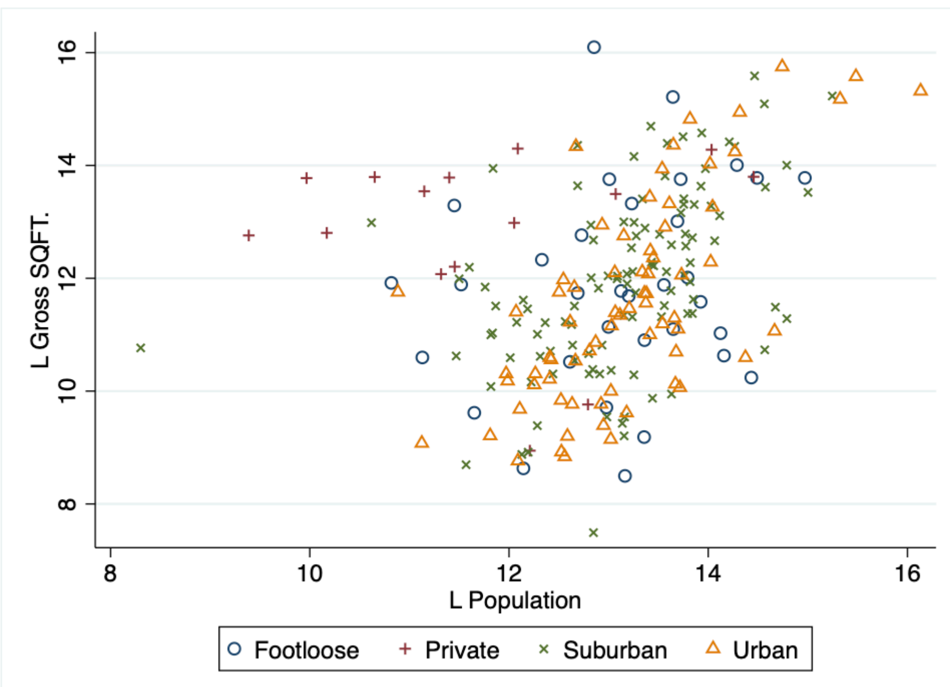

Figure 3: Population vs Capacity. This graph demonstrates the relationship between county population and the capacity within the county, conditional on some data center entry. A county is assigned a type based on what type of data center has the largest share of capacity within the county.

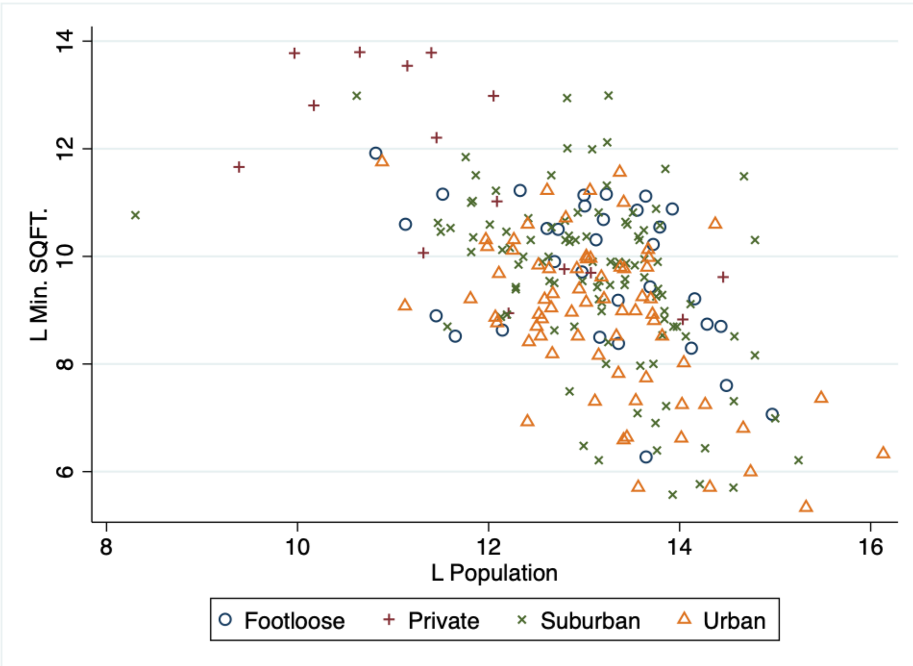

Figure 4: Population vs Minimum SQFT. This graph demonstrates the relationship between county population and the size of the smallest entrant within the county, conditional on some data center entry. A county is assigned a type based on what type of data center has the largest share of capacity within the county.

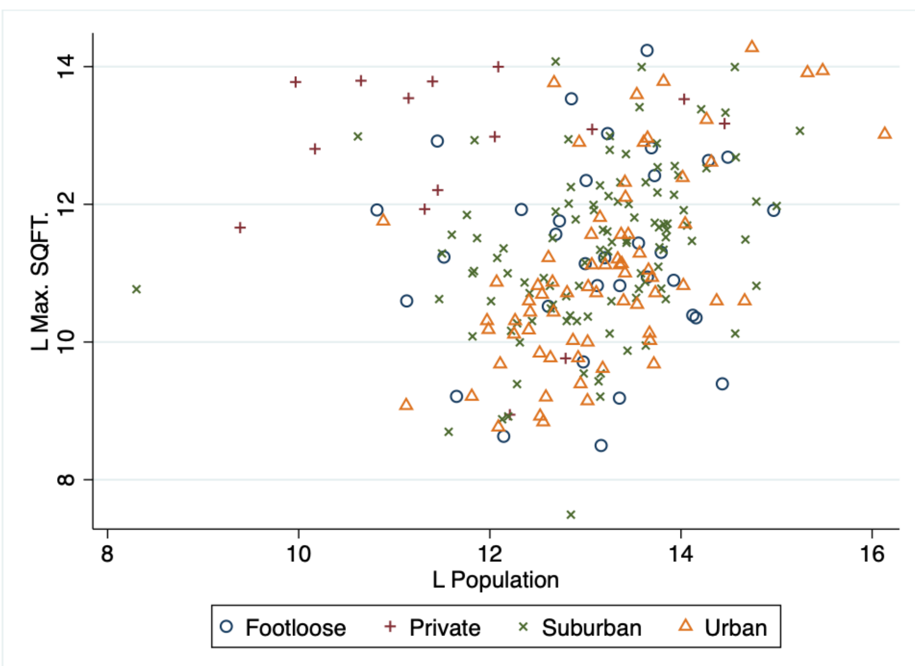

Figure 5: Population vs Maximum SQFT. This graph demonstrates the relationship between county population and the size of the largest entrant within the county, conditional on some data center entry. A county is assigned a type based on what type of data center has the largest share of capacity within the county.