Land Valuation in the Metaverse: Location Matters

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First version: September 29, 2021
This version: July 22, 2024

Citation info:
This is the working paper. Please cite the journal version – available here.

Abstract:
In urban economics, transportation costs are a key determinant of land value. However, in virtual worlds these costs are generally limited by the users' ability to teleport. Drawing from Ahlfeldt et al. (2015) and the concept of attention economies, we propose a theoretical model micro-founded on user behavior. The model suggests that the relative value of land parcels hinges on their potential to attract visitors. Our empirical analysis supports this by demonstrating that location remains crucial in virtual worlds and highlighting the role of the teleportation threshold. We discuss the model's general applicability, reaffirming the significance of location within most virtual worlds.

Keywords: Attention Economy, Locally Weighted Regression, Metaverse, NFTs
JEL Classification: G41, R14, R33

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1 Introduction

Virtual worlds like *Second Life*[1] have shown great commercial potential. People spend significant amounts of time and money in the *metaverse*,[2] where they create their personal avatar and interact with the virtual environment and other economic agents. Investors can buy virtual land, on which they deploy their own structures and applications. In many cases, firms have utilized this to establish businesses and create a space where they can offer goods and services, promote their brands and products, and host events. Some early examples include the opening of a virtual American Apparel store,[3] a virtual Dell PC factory,[4] and the launch of a virtual Toyota model in *Second Life*.[5] More recently, a casino in *Decentraland* (Ordano et al., 2017) has hired people as staff to engage with new customers,[6] both Coca-Cola[7] and Burberry[8] have sold avatar apparel, and several big tech firms have shown great interest in the metaverse.[9] The metaverse is likely to have a lasting impact on the way firms operate and engage with their customers. However, we currently have a very limited understanding of the underlying economics.

The metaverse can be described as "an online collaborative shared space built of 3D environments that leverage high consumer immersion techniques to reduce the perception of technological mediation alongside transferrable and unique digital assets while allowing user-generated digital personas to interact with each other." (Yoo et al., 2023) In its present state, the metaverse consists of various siloed virtual worlds that emulate physical space. Each world operates on its own underlying code, providing considerable flexibility to deviate from natural laws observed in the physical domain. This flexibility enables a distinctive feature common to many virtual worlds: avatars can teleport to any location within these environments quickly, challenging traditional constraints and perceptions of space and proximity.

Despite land use and value in the physical world being closely tied to transportation costs, it is unclear whether the underlying theories (Von Thünen, 1826; Alonso, 1964; Mills, 1967; Muth, 1969; White, 1988; Wieand, 1987; Anas and Kim, 1996; Hoyt, 1939) and the empirical findings (e.g., Heikkila et al., 1989; McMillen, 2003; Tyrväinen and Miettinen, 2000; Mahan et al., 2000; Cho et al., 2006; Bowes and Ihlanfeldt, 2001; Andersson et al., 2010) apply to a virtual reality, where avatars can teleport to any location at a fixed cost. Our study aims to investigate the applicability of traditional theories of land use and value in the virtual domain. Specifically, we seek to answer the question: does location play a significant role in the metaverse?

This paper considers a social virtual world that allows investors to purchase, own, and customize parcels of land to create arbitrary scenes without any artificial constraints other than the avatars' maximum walking speed. In this context, virtual land is inherently commercial, as any demand for other types of land use would need to be explicitly created in the environment's underlying code. By default,[10] there is no demand for residential, agricultural, or industrial land. Avatars simply appear (disappear) when an agent logs in (out) of the virtual world. They also do not need workspace in the digital space. Moreover, virtual land cannot be used to cultivate crops or to build factories that produce goods, and it does not contain any extractable resources. Contrary to land in the physical world, virtual land is not a production factor. Nevertheless, there are many examples of buildings that visually appear like homes, offices, company headquarters, or factories[11] in such worlds, but they usually have a commercial purpose as well. For example, factories allow customers to inspect, customize, and order products on-site, and offices or homes serve as brand ambassador spaces for firms, celebrities, and influencers.

To examine the effect of location on land value, we present a theoretical model, based on the work of Ahlfeldt et al. (2015) and the idea of attention economies (Simon, 1996; Falkinger, 2007). We modify the model to enable us to observe the unique features of virtual worlds. Our theory posits that the value of virtual land is primarily determined by its potential to attract visitors. In a commercial setting, land owners compete for the agents' scarce attention, i.e., their time, making land parcels that attract more potential customers more valuable. The model predicts that land parcels in close proximity to focal points may benefit from visitor spillovers despite the agents' teleportation capabilities.

To test for these locational effects, we analyze a unique data set of 34,358 land sales in the first large-scale, blockchain-based virtual world *Decentraland* (Ordano et al., 2017). The setting allows us to investigate the relationships between the observed land prices and pseudo-geographic, locational characteristics, such as the distances of land parcels to popular locations, including the city center, plazas, districts, and roads.

Econometrically, we begin our analysis with hedonic regression models that examine the impact of distances to focal points on virtual land prices. We then control for the unique transportation costs in the metaverse by re-estimating the models with transformed distance variables that better reflect the underlying economic costs. This approach also allows us to estimate the implied teleportation threshold, which represents the distance at which users switch from walking to teleporting. Discrepancies in the magnitude of the coefficient estimates prompt further examination of potential non-linearities and structural breaks in the relationship between the distance to the central business district (CBD) and land prices. Employing semi-parametric methods, we provide additional evidence that parcel prices below the teleportation threshold are more sensitive to proximity to the central plaza than those farther away. Overall, our analysis highlights the significant impact of visitor spillover potential on the relative prices of land parcels within the virtual world.

To the best of our knowledge, the present paper is the first study, which incorporates these geographical components. Although the importance of virtual economies (Castronova, 2002) and the (economic) research potential of virtual worlds (Bainbridge, 2007) were recognized many years ago, the empirical literature on virtual worlds has been quite sparse. One of the first empirical studies in this field, conducted by Xiaolin et al. (2010), finds a correlation between land prices in *Second Life* and the physical world. More recently, Dowling (2021) investigated the efficiency of a particular virtual land market, but the study does not account for the essential locational characteristics of land parcels.

We are confident that our study is of great interest to researchers, practitioners, and policymakers. Our paper builds on some of the most influential studies and dominant methodologies in the field. Yet, it adds various new ideas and bridges the gap between traditional economics and the virtual domain. It is a novel and interdisciplinary contribution to the urban economics and business literature. From the practitioners' point of view, the study may provide valuable insights into the price-determining factors of non-fungible tokens (NFTs), or more precisely, land parcels in the metaverse. For researchers who are interested in virtual worlds and the metaverse, the study provides a great foundation and interesting results, with insights into the preferences of investors and users. Traditional economists with no particular interest in the metaverse may be intrigued by the unique setting, the novel data set, and the empirical finding that locational preferences are still present, even in a world where transportation costs are capped. Policymakers may be particularly interested in the differences between the physical and virtual settings. They will face the challenge to provide clear and enforceable rules without stifling innovation in this space. To succeed in doing so, they must understand the architecture, the dynamics, and the economics of the metaverse. Our study may provide valuable insights in this regard.

The remainder of this paper is structured as follows: In Section 2 we build our theoretical framework to determine the value of virtual land. In Section 3 we describe our data. In Section 4 we introduce the empirical methods and present our estimation results. In Section 5 we discuss the empirical results and the general applicability of the theoretical model to other virtual worlds, and in Section 6 we conclude.

2 Theoretical Framework

To guide our empirical analysis, we develop a theoretical model in which profit-maximizing land owners compete for the attention of agents that are time-constrained. The virtual world essentially operates as an attention economy (Simon, 1996; Falkinger, 2007) similar to the Web, but it adds a geographic dimension to the otherwise non-spatial nature of content networks. The virtual environment is partitioned into uniform parcels of land arranged in a grid layout, effectively emulating the spatial configuration of an urban setting.

Land owners select their locations within the virtual world and manage their virtual properties by determining the content to be displayed on their land parcels.

Agents make decisions on which locations to visit in an effort to maximize their utility. Given the vast expanse of the virtual world, combined with the agents' limited time budgets and the costs of transportation, it is infeasible for them to explore every land parcel. Therefore, agents are compelled to make decisions about which land parcels to visit, the amount of time to devote to each visit, and the time allocation for transportation.

We consider a virtual world that consists of a finite set of discrete locations, or *parcels*, similar to Ahlfeldt et al. (2015). The land parcels are indexed by $i = 1, ..., S$ and uniquely defined by a pair of coordinates x_i, y_i on a two-dimensional grid. Each parcel has an effective floor space of $A = a \times a$, where a denotes the length of each side. Parcels exhibit no variations in terms of final goods productivity, residential amenities, or floor space. Distinctions solely arise from their location within the virtual world, such as their proximity to landmarks or access to public roads.

Each land parcel is owned by a profit-maximizing land owner. Given that owning land incurs a cost, whether through purchase or rent payments, rational land owners strive to generate revenue to offset or exceed these costs. Revenue depends on the number of agents and effective time spent on their land parcel, meaning that land owners aim to maximize *traffic*.

The virtual world is frequented by H agents, or *users*, who are perfectly mobile within the virtual environment. These agents can employ two distinct modes of transportation. They can either walk at a speed $v0$, or teleport to any parcel within the virtual world after a brief, fixed amount of (loading) time $\bar{\tau}$. Agents are time-constrained and myopic. They repeatedly determine whether they wish to stay at a specific location to earn some utility, or if they prefer to allocate their time for transportation to spend time at a different location instead.

2.1 Land Owners

Land owners can be described as commercially driven and profit-maximizing firms. The profit function for location i is given as:

$$\pi_i = \lambda T_i - R_i - C, \tag{1}$$

where $\lambda = qp_0\eta$ represents the monetization of total time spent T_i by all agents at location i, and consists of the firm's produced output

$q = f(\cdot)$ of a fictional good, the price of the produced good p_0, and the conversion rate η. R_i is the rent at location i and C are other fixed costs, such as the cost of labor independent of the location i.

It is important to note that this profit function deviates from conventional models found in the physical world (e.g., Fujita and Ogawa, 1982). These adjustments stem from the virtual land parcel's exclusive role as a point of sale, distinct from functioning as a production site. Factors influencing production, such as labor (and wages), are not contingent on the location within the virtual domain. Moreover, the production function $f(\cdot)$ may undergo variations based on the firm's business model. For instance, in the case of a firm opting to trade virtual goods like avatar apparel, the design is crafted by a worker in the physical world, and the costs are captured by C. The firm can then establish the profit-maximizing quantity $q = f(\cdot)$ for sale, as virtual goods are not constrained by the limitations of scarce resources.[12] Conversely, if the firm chooses to sell physical goods, such as those sold by a traditional online shop, the cost of labor remains unrelated to the location i within the virtual world as well, and the costs are also encapsulated by C. This highlights the unique dynamics of the virtual world economy, where the focus is on the trade of goods and services within a digital realm rather than adhering to traditional production and distribution paradigms.

The land owners' bid-rent function for a given profit level π is expressed as:

$$\Phi_i = \lambda T_i - \pi - C. \tag{2}$$

Note that in the scenario of perfect competition among land owners, where profits tend towards zero, the bid-rent function simplifies to $\Phi_i = \lambda T_i - C$. In other words, the willingness to pay for a land parcel i increases linearly with the total time spent T_i by all agents.

To boost the total time spent T_i, land owners can employ two main strategies. *First*, they can curate and present engaging content on their land, thereby enhancing the average utility agents derive from spending time at these locations. *Second*, they can choose a location i that reduces the distance to areas attracting a lot of agents, resulting in an increased likelihood of visitor spillovers. While the first strategy may increase total traffic – and thus, the absolute land value – it is completely location-independent because all parcels can equally accommodate the content. However, the second strategy depends on the parcel's individual characteristics which are location-dependent. Thus, relative price differences between land parcels within the virtual world must originate from the differences in the land parcels' visitor spillover potential.

2.2 Agents

In order to understand the visitor spillover potential better, we model the agents' decision-making process that leads to their behavior. Each agent o is assigned an exogenous time budget B_o that limits their overall time that they spend within the virtual world:

$$B_o \geq \sum_{i=1}^{S} t_{io} + \sum_{i=1}^{S} \sum_{j=1}^{S} \rho_{ijo} \tau_{ij}, \tag{3}$$

where t_{io} denotes agent o's time spent on parcel i, τ_{ij} represents the transportation time between j and i, and ρ_{ijo} indicates the number of times agent o moved from j to i.

For agent o, who spends time at location i, the direct utility function U_{io} is given by:

$$U_{io} = z_{io} t_{io}^{\gamma}, \quad \gamma \in (0, 1), \tag{4}$$

where the idiosyncratic utility z_{io} captures the notion that individual agents may have unique reasons for spending time at a particular location, akin to Ahlfeldt et al. (2015). Assuming perfect information, the users are made aware of their realizations of z_{io} as soon as they enter the virtual world. These realizations are drawn from an independent Fréchet distribution:

$$F(z_{io}) = e^{-E_i z_{io}^{-\epsilon}}, \quad E_i > 0,\ \epsilon > 1, \tag{5}$$

where E_i determines the average utility draw at location i, and the shape parameter ϵ controls the dispersion of the idiosyncratic utility.

The parameter γ in Equation (4) defines the concavity of the utility function in time t_{io} and indicates a diminishing marginal utility over time. The general idea is that agents will get bored with experiencing the same content for a long period of time.

The myopic agents repeatedly choose where to spend the next unit of time Δt given their idiosyncratic utility z_{io}, the time t_{io} they had already spent at location i, and the transportation costs to move from j to i. These costs take the form of an iceberg disutility:

$$\theta_{ij} = e^{\kappa \tau_{ij}} \in [1, \Theta], \tag{6}$$

which increases with the commuting time τ_{ij}. The parameter κ controls the size of the commuting cost, and $\Theta = e^{\kappa \bar{\tau}}$ caps the agents' disutility at a maximum value. The disutility is capped at Θ because rational agents will always use the transportation mode that takes less time; that is, if teleporting takes less time than walking, the agents will teleport. Conversely, if it takes less time to walk, the agent will walk. In other words, agents will teleport if they travel distances greater than the *teleportation threshold* $\bar{d} = v\bar{\tau}$.

Agent o decides to visit location i and spend time there, if i offers the highest discounted incremental utility:

$$\begin{aligned} u_{ijo} &= \frac{z_{io}}{\theta_{ij}} \left[(t_{io} + \Delta t)^{\gamma} - t_{io}^{\gamma} \right] \\ &= \frac{\Delta U_{io}}{\theta_{ij}}, \end{aligned} \tag{7}$$

where the disutility θ_{ij} is a discount factor of the incremental utility ΔU_{io}.

This setup can lead to various interesting behavioral patterns. In the simplest case, an agent will choose to remain at their current location to earn some utility. In other cases, they may decide to move to a different location. Depending on the travel time τ_{ij} (or alternatively, the distance $d_{ij} = v\tau_{ij}$), the agent will decide to walk or teleport. Finally, agents may also leave the virtual world. For simplicity, we assume that they will continue to spend time in the virtual world as long as their time budget is not depleted and the incremental utility ΔU_{io} from the upcoming time interval Δt is positive. Consequently, positive incremental utility ΔU_{io} earned in the virtual world is defined as the incremental utility surpassing the threshold incremental utility $\Delta\tilde{U}$ that could be achieved outside the virtual world.

Similar to Ahlfeldt et al. (2015),[13] we can derive the commuting choice probabilities of an agent o moving from j to i:

$$\psi_{ijo} = \frac{E_i \left[\left[(t_{io} + \Delta t)^{\gamma} - t_{io}^{\gamma}\right] / \theta_{ij}\right]^{\epsilon}}{\sum_{s=1}^{S} E_s \left[\left[(t_{so} + \Delta t)^{\gamma} - t_{so}^{\gamma}\right] / \theta_{sj}\right]^{\epsilon}}. \tag{8}$$

The commuting choice probability ψ_{ijo} relies on several factors. These include the accrued time t_{io}, the average utility draw E_i, and the transportation costs θ_{ij} (*bilateral resistance*) in the numerator. Additionally, the accrued time t_{so}, the average utility draw E_s, and transportation costs θ_{sj} for all other potential locations s (*multilateral resistance*) contribute to the denominator. Agents tend to favor locations with a high average utility draw E_i (indicating interesting content), low accrued time t_{io} (little previous experience), and low transportation costs θ_{ij}.

The visitor spillover potential of location i is given as:

$$V_i = \sum_{o=1}^{H} \sum_{j \neq i}^{S} h_{jo} \psi_{ijo}, \quad h_{jo} \in \{0, 1\}, \tag{9}$$

where h_{jo} denotes whether the agent o is currently at location j. V_i can also be understood as a market access index Donaldson and Hornbeck (2016). The value of land essentially derives from its geographic connectedness to markets of varying sizes.

The retention of agents staying at location j is:

$$V_j = \sum_{o=1}^{H} h_{jo} \psi_{jjo}. \tag{10}$$

3 Data

To investigate how visitor spillover potential impacts virtual land value, we have collected cross-sectional data on the locations and prices of land parcels in a specific virtual world. This section introduces said virtual world, outlines its layout, and describes the land auction process, which forms the foundation of our empirical analysis.

3.1 Sample Selection

The particular virtual world that we analyze is called *Decentraland* (Ordano et al., 2017). It was created as the first large-scale virtual world built on public blockchain and smart contract infrastructure and consists of 90,601 unique virtual land parcels. Each parcel corresponds to a square area of 100m^2 (10 by 10 meters). The location of each parcel i is unique and can be described by a pair of coordinates x_i, y_i, where $x_i, y_i \in \{-150, -149, \ldots, 150\}$. Parcels are represented as non-fungible tokens (so-called NFTs), issued on the Ethereum (Buterin, 2014; Wood, 2014) blockchain. The owner of such a token has unambiguous control over the underlying parcel. They can modify its content, offer the parcel for sale on the secondary market, or transfer the ownership rights to another party. The virtual world's assets and applications are stored on a distributed file sharing system.[14]

We have selected this particular virtual world for four main reasons:

First, Decentraland's multi-layered architecture creates a decentralized virtual world. This setup significantly reduces the risks to investors associated with unilateral rule changes by a central operator. Without centralized control, investors are free from sudden, biased interventions that affect the virtual world – either directly through actions or indirectly through rumors and potential hold-up problems. *Second*, the open architecture allows us to easily compile a data set of virtual land prices. Decentraland essentially corresponds to a perfectly observable experiment with significant incentives in place. In other virtual worlds, it is usually much more difficult to get access to these kinds of data for academic research, or there is no real money at stake. *Third*, parcels in Decentraland are identical in size and shape, and they are embedded in a grid structure. The uniformity and distribution are a great advantage for our empirical analysis. *Finally*, Decentraland was the first large-scale blockchain-based virtual world that gained a lot of traction from businesses[15] and other agents.

3.2 World Layout

Decentraland's geographical layout revolves around a symmetric configuration of nine major plazas, as well as 56 community-built districts, a public road system and 43,689 private parcels.

Plazas and streets are considered public spaces. The nine plazas are governed by a Decentralized Autonomous Organization (DAO)[16] and are primarily used as informational hubs or to host large community events. The road system connects plazas, districts, and the outermost regions, and gives the world a familiar structure. The 56 community-owned districts are each governed by their own mayor or DAO-based governments and have their own set of rules. Purposes and themes of such districts range from general business to education, fashion, art, or adult entertainment. The number of parcels assigned to each district is a result of the general interest, measured by the allocation of financial resources by the community before the first land auction. Table 3 in the Appendix summarizes the names, descriptions, and number of parcels assigned to each district. For our analysis, we group the largest districts ($\geq$ 100 parcels) into four categories: *Business*, *Gaming*, *Culture & Education*, and *Politics* based on their names and descriptions.

All parcels not belonging to a plaza, road, or district are considered private and were offered for sale through a public auction.

3.3 Land Auction

Starting on December 15th, 2017 anyone could submit bids to claim one (or more) of the 43,689 private parcels sold in an open-bid English auction. The minimum required bid per parcel was 1,000 MANA[17] or roughly $100 US. The land auction was held off-chain, and the land ownership rights were transferred in exchange for the winning bids after all auctions concluded.

For our analysis, we collect the winning bids for all private parcels. These data can either be reconstructed from the original set of bids or accessed through an Application Programming Interface (API).[18] For this study, we convert all MANA prices to their US dollar equivalents based on the daily exchange rate from coinmarketcap.[19] We plot the observed US dollar prices in Figure 1.

9,331 parcels failed to receive the minimum required bid. These parcels, which are predominantly located in more remote regions of the world, were re-offered through a Dutch auction in December 2018. We exclude these parcels from our analysis for two reasons: *First*, the auction mechanism and the locational features of these parcels differ substantially from the parcels that were claimed during the first auction. This complicates the comparison of the observed prices. *Second*, parcels that were claimed during the first land auction may have affected the prices paid during the second auction. This would require further econometric assumptions.

The observed land auction presents a unique scenario where each winning bid corresponds to one specific parcel during a land-grabbing phase. Given that parcels are identical except for their locations, any price discrepancies must arise from the investors' locational preferences. Unlike analyses in the physical world, this setup eliminates the need to consider parcel size (Colwell and Munneke, 1997), shape, zoning restrictions, or time. The simplicity of the initial land auction offers a direct opportunity to analyze whether location influences investors' decisions in the metaverse.

4 Estimation

In this section, we present reduced-form evidence supporting the qualitative predictions of the model. Specifically, we examine whether the proximity to popular landmarks significantly influences investors' decisions in a virtual world where users can teleport.

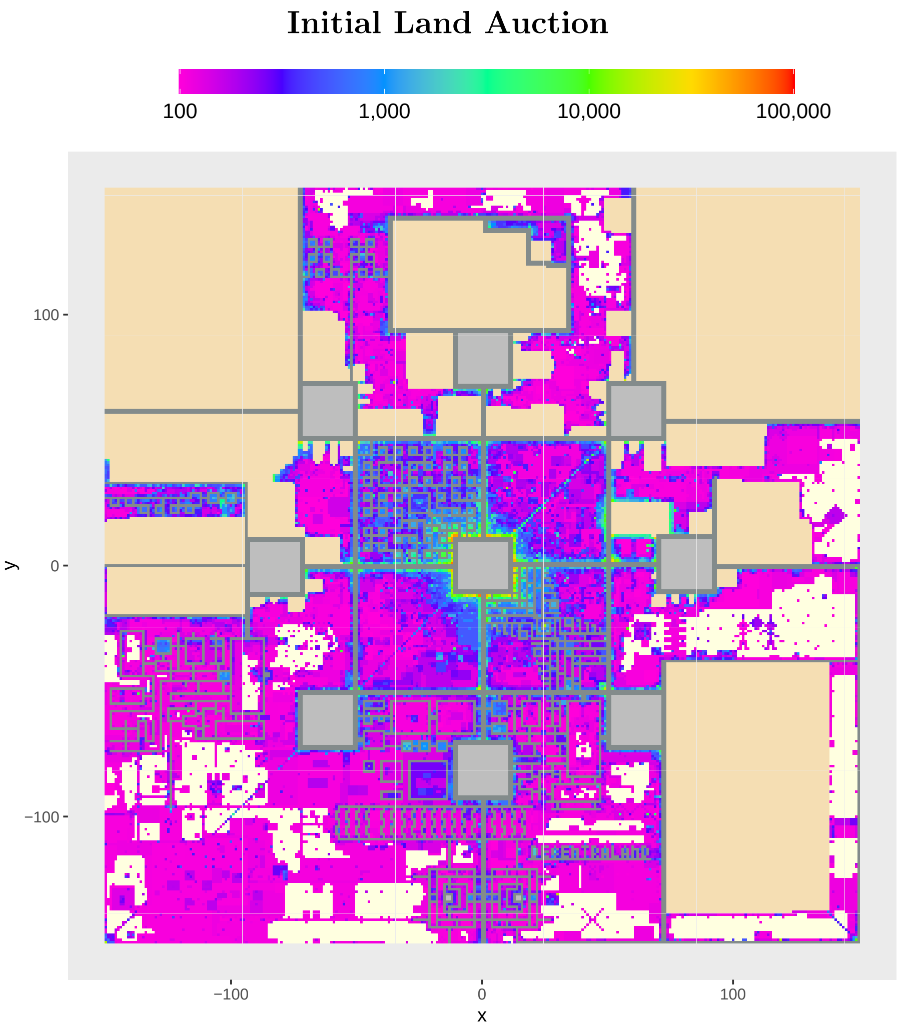

Figure 1: Prices paid (in US dollars) for all $N = 34{,}358$ parcels that were claimed during Decentraland's initial land auction in December 2017. Light grey parcels correspond to the nine major plazas, dark grey parcels belong to the road system, dark yellow parcels belong to one of 56 districts, and light yellow parcels were not claimed during the initial auction.

Essentially, our estimates capture investors' expectations of user behavior and expected visitor spillovers to private parcels. Our analysis focuses on the initial land auction where investors and users were aware of the planned developments for all 56 districts and the nine plaza. However, they lacked similar information regarding the private parcels, which were undeveloped at the time of the auction. Therefore, we infer that investors expected higher activity in the plazas and districts than on the private parcels. As a result, private parcels near these landmarks were expected to experience increased traffic from visitor spillovers compared to private parcels farther away, which is likely reflected in the observed auction prices. Similarly, the main roads connecting these landmarks were also expected to promote visitor spillovers to nearby parcels.

We expect to observe heterogeneous effects between the central plaza and the other eight plazas, as well as among the 56 districts. The central plaza is particularly important, as it serves not only as one of nine community-controlled plazas but also as a natural focal point in the center of the virtual world. In addition, the central plaza serves as the default spawn point for avatars upon logging into the virtual world, similar to a central train station in an urban environment in the physical world. As such, we expect the central plaza to experience a higher level of urban development and visitor density than other locations in the virtual world. This should be reflected in the prices paid for surrounding parcels. The impact of districts on visitor attraction may vary depending on the content they offer. In general, we expect districts categorized under *Business* and *Gaming* to have a more pronounced price impact than those categorized under *Culture & Education* or *Politics*, as *Business* districts are particularly focused on monetization, and *Gaming* districts may be more interesting to the average metaverse user than *Culture & Education* or *Politics*.

A notable feature of our data set is the inherent exogeneity of the explanatory variables. Plazas, roads, and districts existed in the virtual world prior to the land auction, and their locations cannot be affected by the outcome of the auction. This minimizes concerns about causality associated with regressing land prices on their distances to these focal points.

4.1 Preliminary Hedonic Regression Models

To examine the spillover effects of plazas and districts, we initially estimate the following hedonic regression model using Ordinary Least Squares (OLS):

$$\ln(P_i) = \alpha + \sum_m \beta_m \ln(d_{im}) + \sum_n \delta_n \iota_{in} + \nu_i \tag{11}$$

Here, P_i denotes the observed price in US dollars for parcel i, α represents a constant, β_m are m coefficients corresponding to $d_{im} = \upsilon\tau_{im}$ distances in meters, δ_n are n coefficients corresponding to indicator variables ι_{in}, and ν_i is an error term assumed to be independent of the explanatory variables.

We report heteroscedasticity and autocorrelation-consistent (HAC) standard errors (Conley, 1999) to account for cross-sectional dependence among geographically close observations.[20]

For robustness, we estimate several models that utilize different measurements of distance. Model (1), the *Central Distance Model*, employs distances to the center of each plaza and to the nearest road. It controls for the distances to all 56 districts individually, and for parcels situated on the SW-NE diagonal. The inclusion of parcels on this diagonal allows us to control for potential valuation biases from a salience effect due to the symmetrical coordinates x_i, y_i, as depicted in Figure 1. Model (2), the *Perimeter Distance Model*, measures distances to the nearest edge of a plaza, treating adjacent roads as part of the plaza's boundary. This model also accounts for the distance to the closest road not associated with any of the nine plazas, and similarly controls for distances to individual districts and parcels on the SW-NE diagonal. Models (3) and (4) are simplified versions of Models (1) and (2), respectively. While Models (1) and (2) account for distances to all plazas and all districts, Models (3) and (4) specifically measure only the shortest distance to any plaza and the shortest distance to the nearest district within each category. The rationale behind Models (2) and (4) using perimeter distances is to capture a more direct and comparable measure of proximity. For example, while private parcels must maintain a minimum distance of 120 meters from the city center, due to the parcels belonging to the central plaza, they can be situated directly adjacent to a road parcel. Models (2) and (4) reflect investor expectations that proximity to the plaza environment is significant, while proximity to the plaza's center is considered less crucial. Moreover, Models (3) and (4) offer group estimates for the distance to the closest *Business*, *Gaming*, *Culture & Education*, and *Politics* districts. All model estimates are summarized in Table 1.

In Model (1), the coefficient for the distance to the city center exhibits

Hedonic Regression Model Estimates

	Dependent Variable: Log-Price (US Dollars)			
Covariates: Log-Distances (Meters) to	(1) Central Distances	(2) Perimeter Distances	(3) Central Distances (Simplified)	(4) Perimeter Distances (Simplified)
Central Plaza	−1.018***	−0.629***	−0.608***	−0.435***
	(0.109)	(0.055)	(0.057)	(0.036)
Northern Plaza	−0.131	−0.636***		
	(0.847)	(0.110)		
North-Eastern Plaza	0.105	−0.189*		
	(0.250)	(0.104)		
Eastern Plaza	0.254*	−0.025		
	(0.150)	(0.081)		
South-Eastern Plaza	0.161*	0.083		
	(0.087)	(0.054)		
Southern Plaza	0.232***	0.104**		
	(0.078)	(0.046)		
South-Western Plaza	0.024	0.040		
	(0.068)	(0.035)		
Western Plaza	0.569**	0.082		
	(0.238)	(0.155)		
North-Western Plaza	0.357	−0.242*		
	(0.309)	(0.144)		
Closest Plaza			0.008	−0.082***
			(0.040)	(0.021)
Closest Street	−0.197***	−0.191***	−0.162***	−0.159***
	(0.016)	(0.015)	(0.014)	(0.014)
Closest Business District			−0.102***	−0.104***
			(0.021)	(0.021)
Closest Gaming District			−0.069***	−0.069***
			(0.023)	(0.023)
Closest Culture & Education District			0.034**	0.028*
			(0.016)	(0.016)
Closest Politics District			0.078***	0.088***
			(0.022)	(0.022)
Constant	3.792	9.574***	10.087***	9.278***
	(2.558)	(0.764)	(0.329)	(0.221)
Control: Log-Distances (Meters) to All 56 Individual Districts	Yes	Yes	No	No
Control: SW-NE-Diagonal-Dummy	Yes	Yes	Yes	Yes
Observations	34,358	34,358	34,358	34,358
Adjusted R^2	0.379	0.404	0.320	0.368

Table 1: Hedonic regression model estimates using Ordinary Least Squares (OLS). Models (1) and (3) – the Central Distances Models – consider distances to the center of all plazas, while Models (2) and (4) – the Perimeter Distances Models – consider the distances to the closest parcel associated with a plaza. Models (3) and (4) use simpler model specifications where only the distances to the closest plaza and the distances to the closest district per category are considered. Models (1) and (2) control for the distances to all 56 districts individually. Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors in parentheses (Conley, 1999); * significant at 10%, ** significant at 5%, *** significant at 1%.

a significant negative relationship with property prices. Specifically, for every one percent increase in the distance to the city center, the log-price decreases by approximately 1.018 percent. This suggests that properties located farther from the city center tend to command lower prices, echoing the premium often observed for central locations in the physical world. A similar, though numerically smaller, effect is observed for the distance to the closest street, where a one percent increase in distance is associated with a 0.197 percent decrease in prices. However, the distances to the eight other plaza centers and the intercept are either not statistically significant, or they are significant and exhibit an unintuitive sign. In particular, parcel prices appear to significantly increase with larger distances to the southern and the western plaza.

In Model (2), the estimated coefficient for the distance to the closest parcel associated with the central plaza is -0.629, suggesting a 0.629 percent decrease in prices for every one percent increase in the distance to the central plaza. The discrepancy in the magnitude of the estimated coefficient compared to Model (1) can be attributed to the different distance measurements used. Additionally, Model (2) reveals a significant and numerically substantial impact of the distance to the North plaza on log-prices, indicating a decrease of approximately 0.636 percent for every one percent increase in distance to this plaza. However, distances to other plazas do not exhibit significant effects, or they exhibit an unintuitive sign. The coefficient for street distance remains almost unchanged at -0.191.

In Model (3), log-distances to the closest district per category are introduced as controls, rather than the distances to all 56 individual districts. The analysis reveals a significant negative effect of approximately 0.102 percent for every one percent increase in the distance to the closest *Business* district on price. This indicates that as the distance to the closest *Business* district increases, land prices decrease. The distance to the closest gaming-related district also exhibits the expected sign, but a smaller effect than business-related districts. The effect for the distance to the closest *Culture & Education* district is insignificant. Interestingly, the price impact of distance to the closest politics-related district appears to be reversed, suggesting that investors do not value close proximity to these districts. Model (3) does not find a statistically significant effect for the log-distance to the closest plaza on log-prices.

Finally, in Model (4) there is a significant negative effect of the shortest distance to any plaza on log-prices, with approximately a 0.082 percent decrease for every one percent increase in distance. Furthermore, distances to the central plaza, as well as the *Business* and *Gaming* districts, significantly impact log-prices, while the distance to *Culture & Education* districts does not show significant effects in this model. Parcel prices appear to increase with distances to the closest politics-related district once again.

Across all models, our findings support the expected signs of the coefficients for log-distance to the city center and the closest street. However, the magnitude of the relationship between distance to the central plaza and parcel prices warrants further investigation and appears to vary depending on the model specification. Surprisingly, we do not find compelling evidence for the impact of the log-distance to the other eight plazas on land prices, or we even find the contrary of what we expect:

land prices appear to increase with larger distances to some plazas. Districts with a business theme and gaming-related districts demonstrate the anticipated effects on surrounding land prices. In contrast, we do not observe these effects for *Culture & Education* districts, and notably, we even find a reversed effect for politics-related districts.

4.2 Implied Teleportation Threshold

Although we find partial evidence that proximity to certain focal points influences land prices, we do not observe a convincing effect in all cases, particularly regarding the plaza distances. This likely arises due to a notable limitation in the previous models, which assumed that transportation costs always increase with longer distances. However, our theoretical model indicates that transportation costs should be capped due to the teleportation capabilities and optimal behavior of agents. Consequently, we re-estimate the previous models using transformed distance variables that reflect this cap on transportation costs:

$$\ln(P_i) = \alpha + \sum_m \beta_m \ln(min\{d_{im}, \bar{d}\}) + \sum_n \delta \iota_{in} + \nu_i, \tag{12}$$

where $\min\{d_{im}, \bar{d}\}$ transforms the distances by providing an upper bound, i.e., the *teleportation threshold* $\bar{d}$.

To identify the optimal value of $\bar{d}$, we perform a grid search over a range of possible thresholds. This involves re-estimating the models for each value of $\bar{d}$ in the grid and assessing the model fit using the residual sum of squares (RSS). We plot the residual sum of squares of all estimated models with transformed distance variables in Figure 2, and report the estimated coefficients of the models with the best fit in terms of the minimum residual sum of squares (RSS) in Table 2. The table also includes the estimated implied *teleportation threshold* in meters, as well as a bootstrapped standard deviation using a random subsample (25% of the entire sample) and 100 iterations each.

The estimated implied teleportation thresholds are 275.40, 114.57, 462.88, and 453.80 meters, respectively. It is noteworthy that the rightmost RSS values in Figure 2 correspond to the RSS values of the previously estimated models in Table 1 where distances were not transformed. Models (1) and (3) exhibit a sharp decrease in RSS around 120 meters, reflecting the shortest possible distances for private parcels under the Central Distances Models. Thus, we argue that Models (2) and (4) offer more informative insights as they employ comparable distance measurements for plazas and roads. Model (2) suggests a relatively low teleportation threshold of 114.57 meters (or about 11.5 parcel lengths) when considering the closest distance to all nine plazas and 56 districts separately, while model (4) suggests a larger teleportation threshold of 454.80 meters (or roughly 45.5 parcel lengths) when only considering the shortest distance to any plaza and the closest district per district category. The large discrepancies between the implied teleportation thresholds are driven by the different model assumptions.

Upon reviewing the coefficients presented in Table 1 and Table 2, a noticeable difference emerges in the magnitude of coefficients. With transformed distances, coefficients for various log-distance variables generally appear numerically larger compared to the previous estimates. For instance, in Model (1) of Table 2, the coefficient for log-distance to the

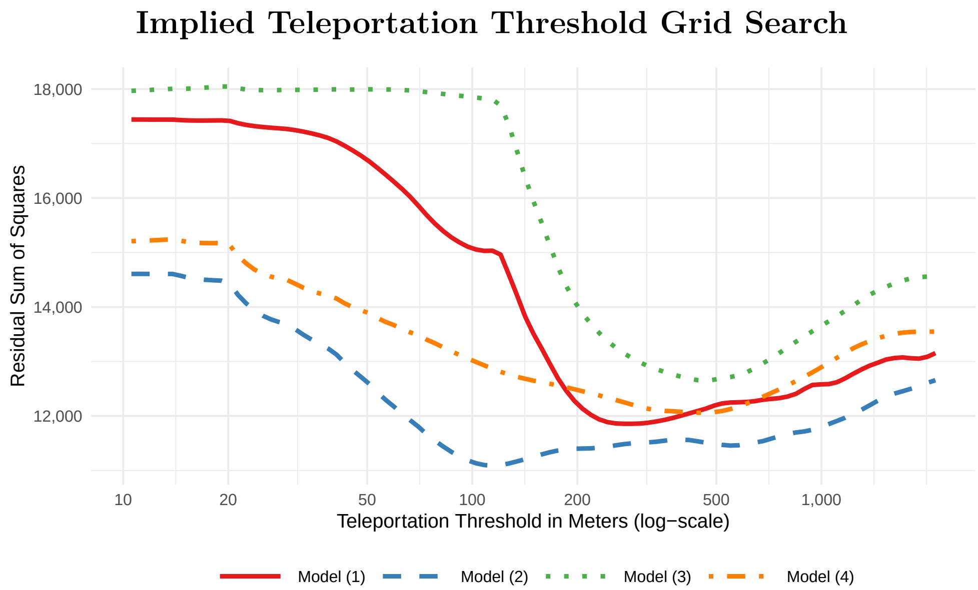

Figure 2: Residual sum of squares (RSS) for Models (1) to (4) using transformed distances $\min\{d_{im}, \bar{d}\}$. The rightmost values correspond to the RSS of the estimated models in Table 1. The minimum RSS per model indicates the estimated implied teleportation threshold in Table 2.

Transformed Distances Model Estimates

	Dependent Variable: Log-Price (US Dollars)			
Covariates: Log-Distances (Meters) to	(1) Central Distances	(2) Perimeter Distances	(3) Central Distances (Simplified)	(4) Perimeter Distances (Simplified)
Central Plaza	−4.606***	−1.736***	−1.946***	−0.787***
	(0.195)	(0.054)	(0.106)	(0.038)
Northern Plaza	−1.026***	−0.434***		
	(0.318)	(0.093)		
North-Eastern Plaza	−1.462***	−0.836***		
	(0.315)	(0.091)		
Eastern Plaza	−0.776***	−0.417***		
	(0.235)	(0.073)		
South-Eastern Plaza	−0.602***	−0.419***		
	(0.215)	(0.067)		
Southern Plaza	−0.791***	−0.347***		
	(0.157)	(0.054)		
South-Western Plaza	−0.572***	−0.395***		
	(0.142)	(0.039)		
Western Plaza	−0.840**	−0.400***		
	(0.359)	(0.145)		
North-Western Plaza	−1.432***	−0.952***		
	(0.531)	(0.118)		
Closest Plaza			−0.364***	−0.193***
			(0.045)	(0.018)
Closest Street	−0.188***	−0.260***	−0.183***	−0.180***
	(0.013)	(0.015)	(0.013)	(0.013)
Closest Business District			−0.140***	−0.130***
			(0.021)	(0.020)
Closest Gaming District			−0.068***	−0.075***
			(0.024)	(0.022)
Closest Culture & Education District			0.017	0.014
			(0.014)	(0.014)
Closest Politics District			0.053***	0.071***
			(0.019)	(0.018)
Constant	75.320***	36.972***	20.364***	12.028***
	(4.892)	(1.216)	(0.626)	(0.230)
Implied Teleportation Threshold (Meters)	275.401	114.567	462.883	453.8
	(26.098)	(3.01)	(19.963)	(35.845)
Control: Log-Distances (Meters) to All 56 Individual Districts	Yes	Yes	No	No
Control: SW-NE-Diagonal-Dummy	Yes	Yes	Yes	Yes
Observations	34,358	34,358	34,358	34,358
Adjusted R^2	0.446	0.482	0.410	0.437

Table 2: Transformed distances model estimates with distance variables $min\{d_{im}, \bar{d}\}$ using Ordinary Least Squares (OLS). The reported models minimize the residual sum of squares given the implied teleportation thresholds. Bootstrapped standard deviations in parentheses for the estimated implied teleportation thresholds. Models (1) and (3) – the Central Distances Models – consider distances to the center of all plazas, while Models (2) and (4) – the Perimeter Distances Models – consider the distances to the closest parcel associated with a plaza. Models (3) and (4) use simpler model specifications where only the distances to the closest plaza and the distances to the closest district per category are considered. Models (1) and (2) control for the distances to all 56 districts individually. Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors in parentheses (Conley, 1999) for all coefficients; * significant at 10%, ** significant at 5%, *** significant at 1%.

city center stands at -4.606, a considerable increase from the coefficient of -1.018 observed in Model (1) of Table 1. This discrepancy implies an even more pronounced impact of distance on property prices when teleportation is considered.

While Table 1 provides only partial support for our predictions, as the coefficients associated with plaza distances are mostly insignificant or exhibit an unintuitive sign, the estimates in Table 2 provide evidence supporting our hypothesis of a decreasing price effect with longer plaza distances. Across multiple plaza distances in Table 2, the coefficients are statistically significant and consistently negative, indicating that properties farther away from plazas tend to have lower prices. This contrast suggests a more nuanced understanding of how proximity to different plaza locations influences property values when considering teleportation.

The estimates for the distances to the closest road and the four district categories are comparable between Tables 1 and 2, both in magnitude and significance. This indicates a consistent estimation of the relationships between these log-distance variables and virtual land prices independent of the consideration of teleportation.

4.3 CBD-Gradient and Robustness Checks

Given the numerical disparities in the coefficients for the log-distance to the central business district (CBD) in Tables 1 and 2, we delve deeper into the relationship between the log-distance to the CBD and land prices.

First, we undertake a re-estimation of the hedonic regression model in Model (1) without transformed distance variables using a Generalized

Additive Model (GAM) (Hastie and Tibshirani, 1987; Wood, 2020) with cubic regression splines for the log-distance to the city center, while all other terms enter the model parametrically as controls. The resulting estimates for the CBD-gradient are visualized in Figure 3 and compared to the best fit of a linear model and a second-degree polynomial, both without controls. The figure highlights that the linear model appears to severely underestimate parcel prices in close proximity to the center. Employing a more flexible approach using GAM reveals a more nuanced relationship, indicating that parcels near the city center exhibit a much more pronounced sensitivity to changes in distance, with property prices declining rapidly in such vicinity. The estimated implied teleportation threshold acts as an approximate breakpoint, where this effect appears to diminish, resulting in a shallower gradient for large distances from the center. The figure sheds light on the discrepancies observed in the estimates presented in Tables 1 and 2, supporting the notion that parcels situated farther away from the city center do not experience a comparable impact on prices attributable to the proximity to the city center, possibly due to the two transportation modes. We present similar figures for the other model specifications in the Appendix, yielding similar findings. Overall, the second-degree polynomial appears to roughly mimic the GAM estimates. The estimated coefficients for the parametric terms in all GAM models are reported in Table 4 in the Appendix. They are generally in line with the previous findings and the predictions of our theoretical model.

Second, we employ Locally Weighted Regression (LWR) (Cleveland, 1979). We estimate one regression model at every location where a sale

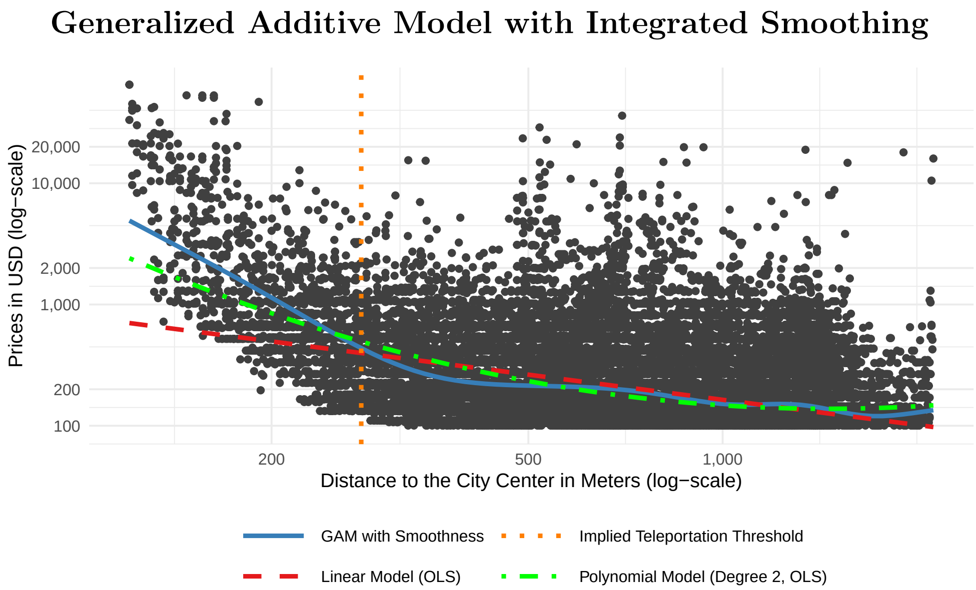

Figure 3: Generalized Additive Model (GAM) employing cubic regression splines for the log-distance to the city center, with parametric controls from Model (1) – the Central Distances Model – as detailed in Table 1. This depiction includes comparisons with linear and second-degree polynomial models. The estimated implied teleportation threshold from Table 2 is also shown. Coefficients for parametric terms are provided in Table 4 in the Appendix. For figures related to alternative model specifications, refer to Figures 6, 7, and 8 in the Appendix.

occurred with a Gaussian kernel utilizing a "leave one out"-validated bandwidth parameter of 130.38 meters. This method addresses the spatially varying impact of the log-distance to the CBD on parcel prices. A two-step procedure (Mei et al., 2004) is employed to estimate the spatially varying coefficients, while all other terms from Model (1) enter the model parametrically as controls. The estimated spatially varying coefficients are illustrated in Figure 4. As anticipated, the coefficients retain a negative sign across the entire virtual world, indicating a general trend where parcel prices decrease with longer distances from the city center. However, in line with our previous observations, this effect appears to be more pronounced in proximity to the city center. We report the estimated coefficients of the parametric terms in the Appendix in Table 5, where we also provide similar Figures 9, 10, and 11 under the model specifications of Models (2) to (4). Overall, the estimates for the other eight plazas, the closest road and four district categories are consistent with our previous findings.

Third, using locally estimated scatterplot smoothing (LOESS), we plot a kernel-smoothed price surface of the observed land prices. We specify a span of 0.05 and tricubic weighting, thereby utilizing 5% of the data points to influence the fitting at each point in the model. This allows for a fine resolution in capturing local price variations related to the geographic location. The predicted values from the LOESS model are subsequently plotted in Figure 5. The visualization illustrates the relationship between spatial coordinates and the observed log-prices, accentuating price elevations in areas surrounding the nine plazas and certain districts, with a notable peak near the central plaza.

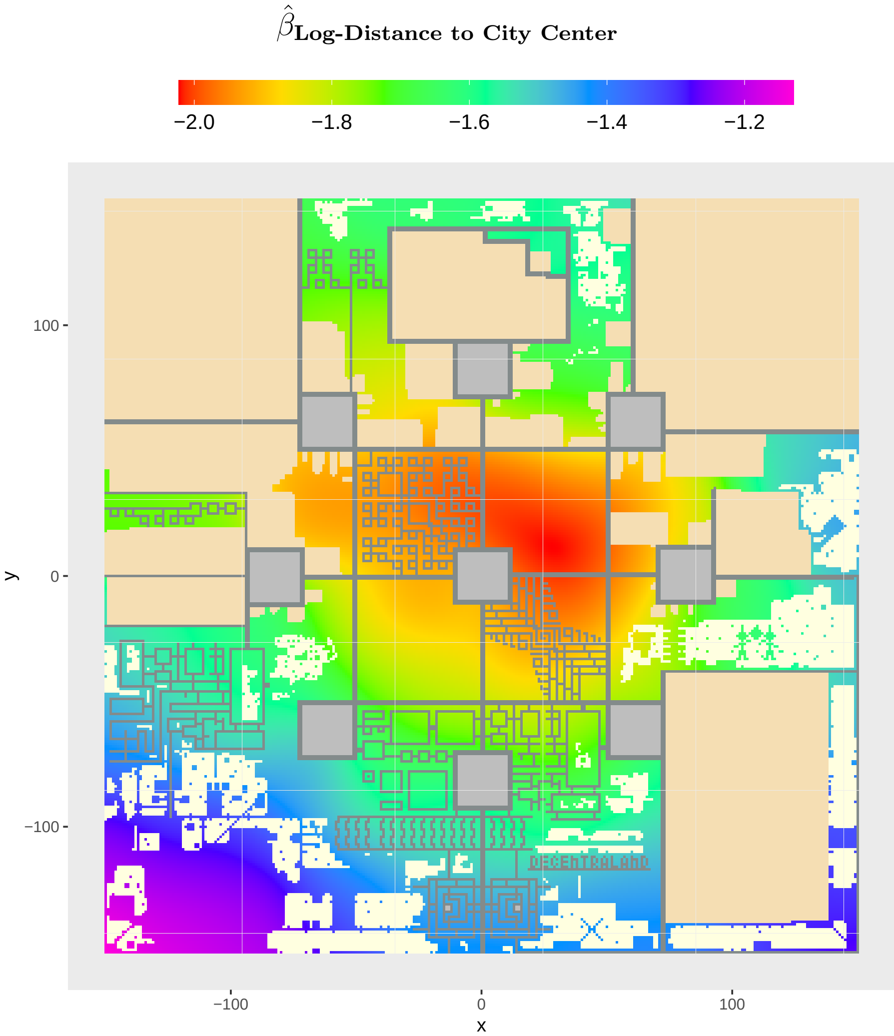

Figure 4: Locally Weighted Regression (LWR) (Cleveland, 1979) results for the estimated coefficients of the log-distance to the city center using Weighted Least Squares (WLS) with a Gaussian kernel utilizing a "leave one out"-validated bandwidth parameter of 130.38 meters. The other terms from Model (1) – the Central Distances Model – in Table 1 enter parametrically as controls. Coefficients for parametric terms are provided in Table 5 in the Appendix. For figures related to alternative model specifications, refer to Figures 9, 10, and 11 in the Appendix.

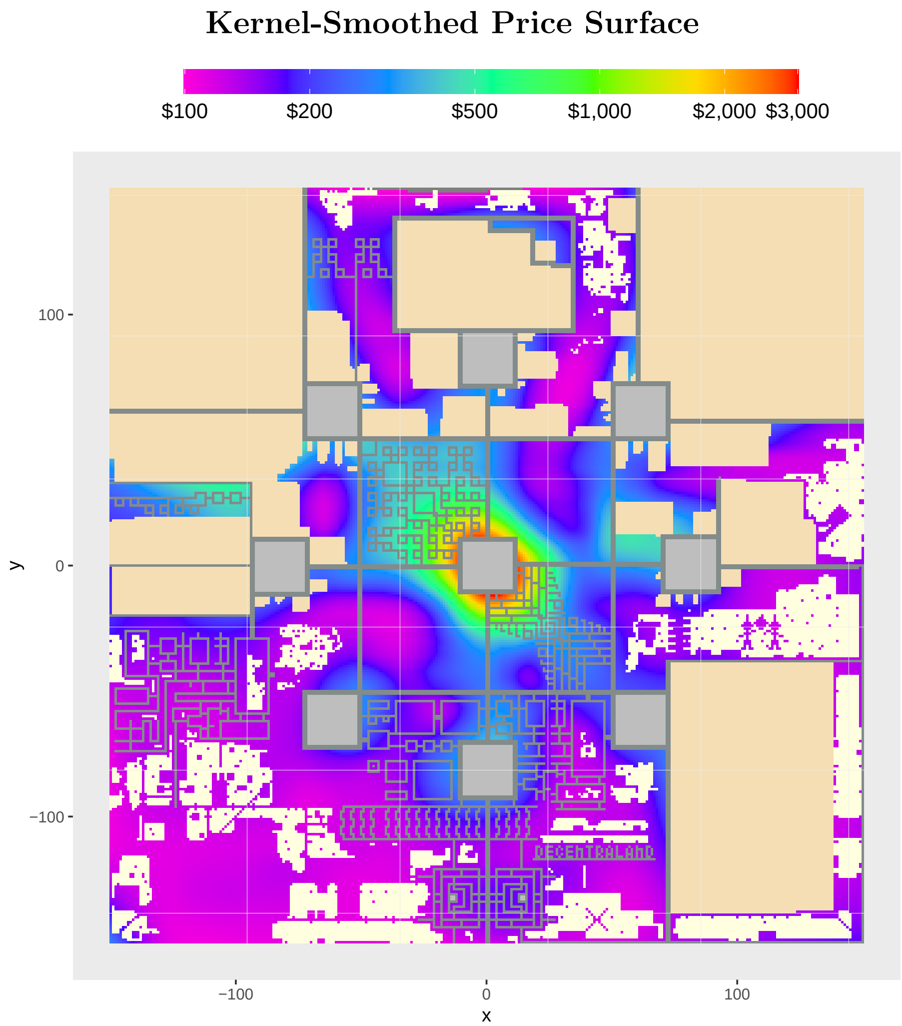

Figure 5: Kernel-smoothed price surface from predicted values using Locally Estimated Scatterplot Smoothing (LOESS) with a span of 5% and tricubic weighting.

Finally, to account for investor-specific preferences, we utilize our data set's capacity to incorporate dummy variables corresponding to the Ethereum address of each individual buyer. This adjustment allows us to reassess the linear models presented in Tables 1 and 2 by substituting the intercepts with those specific to individual investors.[21] We utilize the estimated implied teleportation thresholds from Table 2 to get comparable results, and present the estimated coefficients for all distance variables in Tables 6 and 7 in the Appendix. Controlling for these unique investor characteristics reveals no significant impact on our findings.

5 Discussion

Urban economic literature provides strong evidence that transportation costs are a main factor in investors' locational choices, and thereby significantly affect land prices. In this paper, we study a virtual world, in which transportation costs are capped. Users can either walk, for a cost that increases in distance, or choose to teleport for a distance-independent, fixed cost that effectively functions as an upper cost ceiling. We present empirical evidence indicating that, even in such contexts, locational preferences remain strong. In a commercial setting, investors are willing to pay a premium for land parcels anticipated to attract a higher number of visitors.

This effect can be attributed to the visitor spillover potential of land parcels. Without additional artificial constraints, there is no need for residential buildings or industrial manufacturing sites in a virtual world. Instead, virtual land parcels predominantly serve commercial purposes, such as advertising and sales. This effectively creates attention economies, where land parcels in close proximity to focal points are more likely to get an additional visitor influx through spillover effects, thereby increasing the value of these land parcels.

We first analyzed this relationship in a theoretical model, inspired by Ahlfeldt et al. (2015). We adapted the model to capture the characteristics of the virtual setting. Specifically, we introduced capped transportation costs and incorporated a time budget constraint, along with multi-period decision-making on the part of the users. Similar to Ahlfeldt et al. (2015), we assume that agents get an idiosyncratic utility drawn from a location-specific distribution. The model allows us to microfound visitor spillover effects and show why commercially driven land owners, whose profits depend on the visitor count, have strong locational preferences.

Using data from Decentraland's initial land auction, we conducted reduced-form empirical analyses. The empirical results support the qualitative predictions of the model and provide strong evidence, that location matters even in a setting where agents can teleport. These effects are consistent across all of our main model specifications and robustness checks.

Empirically, we started our analysis with hedonic regression models akin to approaches employed in traditional urban economics. While we find some support for the hypothesis that popular landmarks influence land value, we do not find a compelling effect for all landmarks. In particular, while the city center, roads and the *Business* districts demonstrate a substantial impact on land prices, we do not observe convincing effects for the other eight plazas. However, this initial approach overlooks one of the main characteristics of the virtual world: the users' ability to teleport. Teleporting effectively caps the transportation costs in the virtual world. To address this limitation, we re-estimate our models using transformed distance variables that better reflect the transportation costs inherent in the virtual world. Through these re-estimated models, we uncover more compelling and highly significant effects in accordance with our model. Moreover, we derive parameter estimates for the implied teleportation threshold $\bar{d}$ and shed light on the influence of the city center on parcel prices, which appears more substantial than initially assumed. Motivated by these initial findings, we pursued a deeper exploration of this relationship using semi-parametric methods. The outcomes of these models provide further support for the concept that the gradient near the city center, within distances where agents would opt to walk, exhibits a sharp decline, indicative of significant influence. However, as distances increase beyond this threshold, the gradient becomes flatter, suggesting a diminished impact on parcel prices.

Our empirical findings originate from the initial land auction of one specific virtual world. These numerical estimates can differ across various virtual environments and may even change over time for this particular world. Despite these variations, we argue that our theoretical model reinforces a consistent qualitative finding: location matters in most metaverse settings. Only in the complete absence of transportation costs, agents will disregard geographical relationships, opting to always teleport to locations where their discounted incremental utility is maximized. Any positive value for $\bar{d}$ implies that agents exhibit tendencies to prefer visiting land parcels in close proximity, as transportation costs are lower for these shorter distances.

The parameter $\bar{d}$ is likely to vary across different implementations of virtual worlds and may change over time due to technological advancements. In particular, faster loading times would lead to a decrease in $\bar{d}$. However, there are limitations to this progress. Achieving a $\bar{d}$-value of zero is highly improbable, as it would require eliminating all forms of frictions, including user input. Nevertheless, it should be rather unsurprising that our findings cannot be generalized to cases with $\bar{d} = 0$.

Certain influences of the World Wide Web persist even in environments characterized by geographical connections and locational preferences. Throughout our models, we find a significant positive price impact of the control variable "SW-NE diagonal." In the context of our model, parcels on the SW-NE diagonal do not necessarily have a higher spillover potential. Instead, there seems to be a salience effect due to their equal x and y coordinates. We suspect that investors see the parcels' coordinates as the virtual world's address space, effectively functioning as domain names that facilitate teleportation. Our empirical models suggest a higher willingness to pay for parcels with more salient coordinates. We speculate that in any virtual environment where teleportation is feasible, the prevailing dynamics might represent a fusion of principles from both the World Wide Web and traditional urban economics. However, we would like to emphasize that this discussion point should be seen as a mere hypothesis that deserves a paper of its own.

Moreover, we would like to highlight some limitations of our model. These may be good starting points for model extensions and future research, including studies on the secondary market. *First*, $\bar{d}$ may vary on an individual level, based on the users' hardware specifications and network connections. While we can estimate the implied "global" teleportation threshold, we do not know the individual values. Future studies could explore the user side, use hardware specifications and network connections as a proxy, and exploit this heterogeneity to further explore the effect of the teleportation threshold. *Second*, our model is based on the assumption that users always opt for the least expensive mode of transportation. However, preferences such as the immersive experience of navigating a 3D environment without loading screens or the convenience of travel via coordinates might influence this choice. Therefore, our estimates should be seen not as definitive boundaries between the two modes, but as approximations of what investors anticipated about user preferences and hardware capabilities. Further research could focus on distinguishing these factors more clearly. *Third*, businesses may leverage the dynamic nature of the virtual environment to relocate frequently and at lower costs, increasingly relying on pop-up stores and temporary events for customer engagement. They might also strategically cluster not only near any high-traffic locations but also around experiences that offer similar content. This approach would allow them to more precisely target agents who have a specific interest.

Despite these limitations, we are confident that this paper provides valuable insights and can serve as a robust foundation for future research.

6 Conclusion

The present paper is the first to study the relationship between location and land value in the metaverse. Despite being intangible, virtual worlds are much more than gimmicks and often attract a large number of users who spend substantial amounts of time and money in the metaverse. In the absence of artificially introduced constraints, the land use in the metaverse will be commercially driven, and as such, the visitor spillover potential directly influences the value of land. Land parcels in close proximity to other land parcels that attract a lot of users will be more valuable to land owners. This may be counter-intuitive at first, given that agents in the virtual world can teleport. In our paper, we show theoretically and empirically that location plays an important role because teleportation is typically not costless. Thus, location, or more precisely proximity, matters in the metaverse.

Acknowledgements

We would like to extend our gratitude to Editor Stephen Gibbons and the two anonymous reviewers at the *Journal of Economic Geography* for their insightful comments and suggestions, which significantly improved the paper. We also thank Emma Littlejohn, Tobias Bitterli, Matthias Nadler, Jonas Ruchti, and Andreas Arnold for their meticulous proofreading of the manuscript. Additionally, we are grateful to Yakov Amihud, Aleksander Berentsen, Pascal Gantenbein, Christian Kleiber, Alfred Lehar, Jeffrey Macher, Wolfgang Schäfers, and David Yermack for their valuable input during our discussions. All remaining errors are our own.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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Endnotes

1. See https://secondlife.com/

2. The term *metaverse* refers to Neal Stephenson's 1992 novel *Snow Crash* and is often used synonymously for persistent, shared, three-dimensional virtual spaces.

3. See https://web.archive.org/web/20080402105413/http://secondlife.com/newsletter/2006_06/html/developer.html

4. See https://www.delltechnologies.com/en-us/blog/3555-2/

5. See https://www.reuters.com/article/businesspro-toyota-scion-dc-idUSN0836455020070208

6. See https://www.coindesk.com/this-casino-in-decentraland-is-hiring-for-real

7. See https://www.coca-colacompany.com/news/coca-cola-nft-auction-fetches-more-than-575000

8. See https://www.burberryplc.com/en/news/brand/2021/Blankos.html

9. In the place of many, see Horizon Worlds at https://www.oculus.com/horizon-worlds/ by Meta.

10. Some developers may use the underlying code's flexibility to impose additional constraints, like avatars having basic needs, like food and shelter. In such cases, further economic considerations arise. However, in our study, we specifically focus on a virtual world where the main economic consideration lies in the transportation costs for avatars.

11. See, apart from the previous examples, Adidas' presence in Second Life https://web.archive.org/web/20061207151431/http://www.

3pointd.com/20060819/adidas-reebok-runs-to-second-life/, IBM's "secret" island https://www.theregister.com/2006/09/21/ibm_secret/, or Reuter's news bureau https://web.archive.org/web/20070529034144/http://blogs.electricsheepcompany.com/chris/?p=150

12. It is noteworthy that firms can leverage non-fungible tokens (NFTs) to craft virtual goods that are verifiably scarce and immune to replication.

13. Since the discounted incremental utility u_{ijo} is a monotonic function of the idiosyncratic utility z_{io}, which has a Fréchet distribution, it follows that the discounted incremental utility u_{ijo} also has a Fréchet distribution.

14. Originally, the content was planned to be stored on IPFS (Benet, 2014). Decentraland now uses its own dedicated network of servers. Anyone can setup their own server and enter the network, but the decision to include them in the decentralized file-sharing system is made by Decentraland's Decentralized Autonomous Organization (DAO).

15. See Sotheby's virtual gallery https://decentraland.org/blog/announcements/sotheby-s-opens-a-virtual-gallery-in-decentraland/ or Atari's Casino https://finance.yahoo.com/news/atari-casino-launches-virtual-party-133000509.html

16. A decentralized governance body that allows its members to make policy decisions.

17. A cryptocurrency designed specifically for economic interactions in Decentraland.

18. See https://thegraph.com/legacy-explorer/subgraph/decentraland/marketplace or https://docs.decentraland.org/

market/api/#parcels

19. See https://coinmarketcap.com/currencies/decentraland/

20. We use truncated kernel weights with a threshold of 100 meters. The average sold private parcel has 211.38 other observations within this distance.

21. Note that Ethereum addresses are pseudonyms. While we can be sure that one address does not corresponds to multiple investors with different preferences, we cannot outrule that one particular investor operates under multiple addresses.

Appendix

Districts Summary

Name	Description	Category	Size
AETHERIAN Project	Aetherian City will be one of the main attractions for visitors and dwellers of Decentraland, as it intends to be the largest cyberpunk-agglomeration of the metaverse.	Politics	8008
Vegas City	A digital sin city, party town gambling district of Decentraland. Designed in a style that emulates the Vegas strip, lies a long row of casinos, shopping, concert and performance halls, nightclubs, and sin.	Business	6776
Dragon City	A perfect combination of China's ancient culture and Western modernization, a reflection of both the Eastern and Western civilizations.	Culture and Education	6485
Fashion Street	Bring top fashion brands (Gucci, Prada, Ralph Lauren etc.) in DCL. Each store will give DCL users a high sensory shopping experience.	Business	2098
Red Light District	A district within the Decentraland to help contain/manage/curate Adult services such as; Adult Live-chat, VR pornography, dating services and Adult themes e-stores.	Business	2001
Decentraland University	Create the definitive centre of education in Decentraland.	Culture and Education	1550

Dragon Kingdom	We are thinking of open a district called Dragon Kingdom where Chinese people can get together to share culture, value and language. but we also welcome people from all over the world.	Culture and Education	1187
Decentraland Conference Center	A conference center in a natural, sylvan setting.	Business	799
The Battleground	An Environment for PvP, RPG and RTS Gaming within Decentraland	Gaming	668
Festival Land	This district is for people who want to make a Festival city in Decentraland.	Gaming	473
Virtual Reality Shopping District	VRS District bridges the gap between Decentraland, district0x and eCommerce store owners by acting as a resource to high-end businesses interested in creating their own Virtual Reality Shop.	Business	417
Greenpoint: A Meeting Point for Grassroots Movements	Eventually dissolved	Politics	414
The Crypto Valley	We introduce a virtual Crypto Valley to break up the geographic constraints and provide free access to anyone in the world. It is a large area dedicated to Crypto projects, either existing or upcoming ones.	Business	301
Amusement Park with Carnival Games	An amusement park site in Decentraland, complete with rides, carnival games, gardens, and so on.	Gaming	284
Central Market Place	Set up a central open-air marketplace where vendors can actively sell in-app goods	Business	279

The Forest	Just a bit of quiet, wild and beautiful nature in the crowded and noisy city.	Culture and Education	237
SciArt Lab	Research and Development Lab for the open exploration of Science, Art and Technology.	Culture and Education	208
Decentraland Museum	Create the best place to showcase 2D, 3D and any sort of artwork in Decentraland.	Culture and Education	170
The Anarchist International - (A-Squat)	This district is a refuge for Anarchists to gather outside the Statist-Corporate systems they are battling against for the liberation of humankind.	Politics	167
Bittrex Tomorrow	There will be a skyscraper for each crypto exchange which lists MANA as a token, the height of the buildings will be updated each day with the total volume of MANA traded respective to the exchanges. The walls will plastered with info on each transaction which took place the previous day.	Culture and Education	155
Fluffy DC	Have you already dreamt about a world filled with extra cute kitties? We will make this dream a reality.	Gaming	151
Voltaire	The virtual representation of the Voltaire House	Politics	100
Engineering Park	An area where engineers can meet to discuss, explore, share and showcase ideas. These ideas could be related to the classical branches of engineering or to new branches and possibilities that nobody has even thought of yet.		85
Freedom City	Eventually dissolved		83

SUREAL District	Eventually dissolved	66
Yoga Center	Organize daily yoga classes in a quiet and relaxing environment.	64
Arena: A Futuristic Urban Hotbed of Creativity	Arena is an urban community and hotbed of creativity. This is somewhere for like minded people to move forwards in VR as a loose creative collective.	58
DCL China City	A district where Chinese people can get together to share culture, value and lauguage.	56
Hacker City	A place for developers to gather and build the earliest scripts and items that will be used in Decentraland.	52
InnerGlitch - Science, Technology and Discovery	Eventually dissolved	51
Central Business District	Eventually dissolved	41
Chobury - Democratic City for All	Chobury is designed to be Democratic city that has social spaces, residential areas and commercial areas.	39
Music Hub	The district of musicians, fans, producers, and media. Come to listen to the latest tracks produced by residents, stay for live concerts.	34
EcoGames	We have 3D artists and game developers from around the world who are ready to implement multiplayer mini games.	30
Mother Russia Land	First land for Russian community	29
Democratic People's Republic of Yetepey	This district will aim to work together and realize the goals of Supreme Leader Yetepey.	28

Star City	Aims to establish a city with houses, businesses, community centers, casinos, shops, and so much more.	28
Decentramon	Eventually dissolved	25
Virtual Sand Hill Road	Eventually dissolved	22
VARC - A District for All Things Architecture	VARC will be a district for Architectural professionals, students, hobbyists, and admirers. I envision this district having many roles and projects under four main categories: Presentation, Education, Design, and Commerce.	19
Tech Sector: A Home for Developers	Eventually dissolved	19
War Thunder Community Park	Eventually dissolved	16
SF Zone - A Home for Science Fiction Fans	Eventually dissolved	11
Shwedagon Pagoda	Full size - beautiful Swedagon Pagoda - 100% replica of a real one	11
The Chill Zone	Eventually dissolved	10
Anarchy	Every LAND bought here must COMMIT to let anyone build whatever he wants in this land. We can add some anti-vandalism thing here later if necessary.	9
Hunted District	An area dedicated to what scares us the dark side of thing and anything related to horror. The town will host various genres and themes such as goar, ghost, zombies, cults, among other horror subjects.	9

Toke Social: A Resort for Cannabis Connoiseurs	An artistic style lounge for cannabis smokers to hang around, talk non-sense, and view the world from a different lens.	8
E for EVERYONE	EVERYONE, will be a no sale/no ads zone - a series of explorable sandboxes with limited goals, focused on open play.	8
Star Kingdom	A community in Decentraland for the micronation called the Star Kingdom.	8
Embassy Town	Eventually dissolved	8
NEO TOKYO	Eventually dissolved	8
The Whale Club	Eventually dissolved	7
Design Quarter	Core hub for Modern Design and Visual Identity in VR. Center of Excellence for Virtual Arts from concept to completed construction.	6
Alvy Gardens	Eventually dissolved	5
Little India (Bharat)	Eventually dissolved	5

Table 3: Names, number of parcels and descriptions of all 56 community-built districts in Decentraland based on information from Decentraland's GitHub repository and the District API. Some districts were dissolved after the initial land sale.

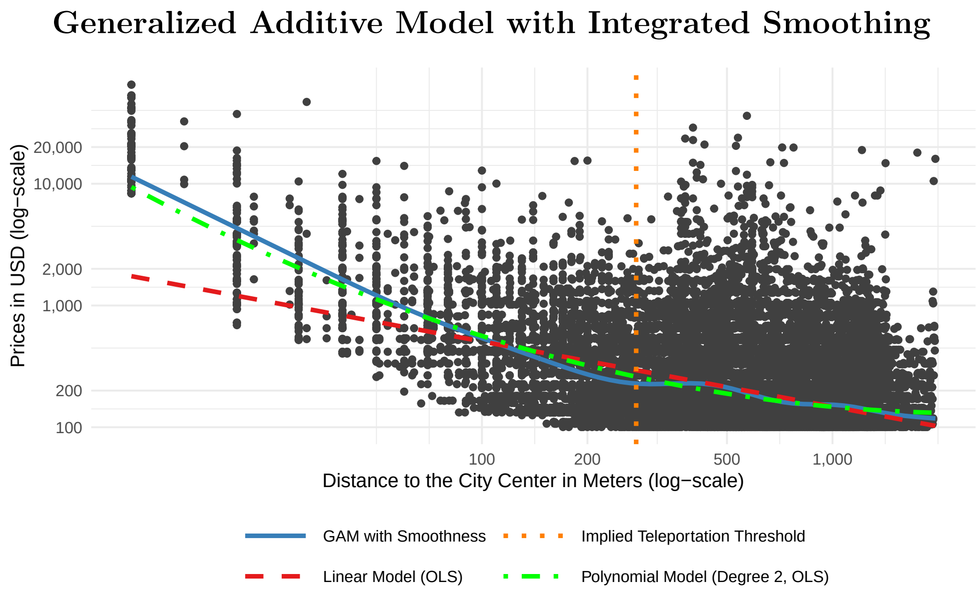

Figure 6: Generalized Additive Model (GAM) employing cubic regression splines for the log-distance to the city center, with parametric controls from Model (2) – the Perimeter Distances Model – as detailed in Table 1. This depiction includes comparisons with linear and second-degree polynomial models. The estimated implied teleportation threshold from Table 2 is also shown. Coefficients for parametric terms are provided in Table 4 in the Appendix. For figures related to alternative model specifications, refer to Figure 3 in the main text, or Figures 7 and 8 in the Appendix.

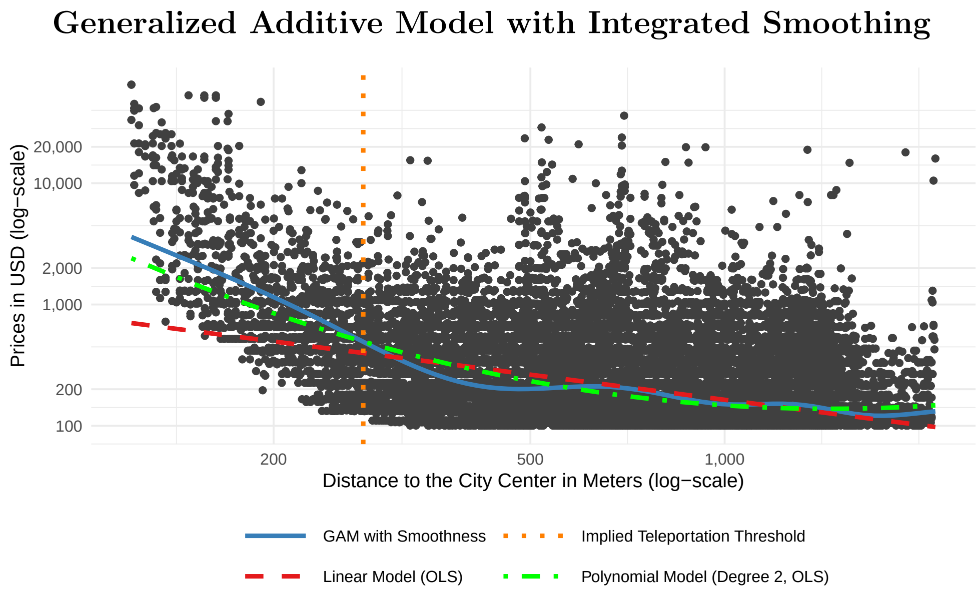

Figure 7: Generalized Additive Model (GAM) employing cubic regression splines for the log-distance to the city center, with parametric controls from Model (3) – the Simplified Central Distances Model – as detailed in Table 1. This depiction includes comparisons with linear and second-degree polynomial models. The estimated implied teleportation threshold from Table 2 is also shown. Coefficients for parametric terms are provided in Table 4 in the Appendix. For figures related to alternative model specifications, refer to Figure 3 in the main text, or Figures 6 and 8 in the Appendix.

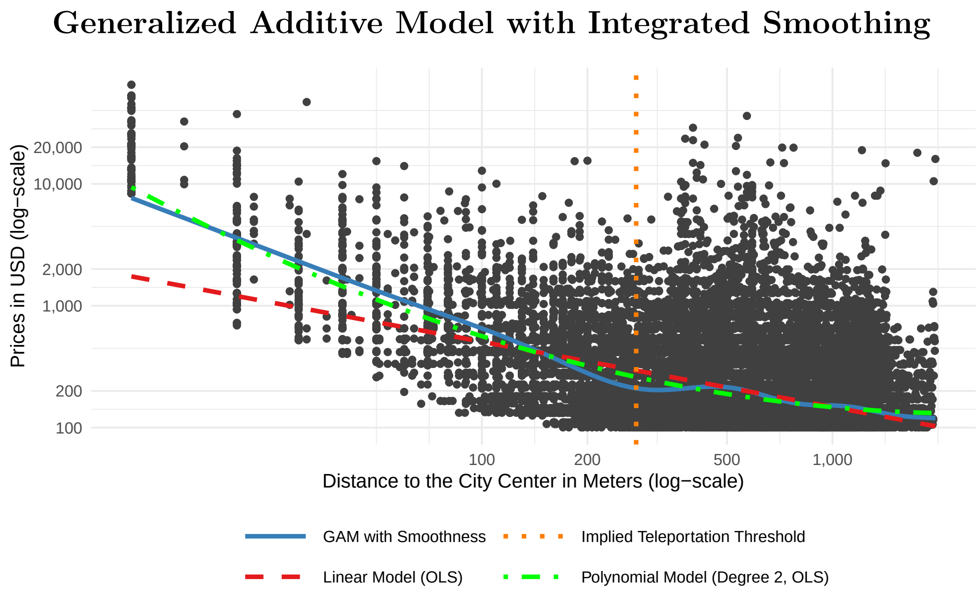

Figure 8: Generalized Additive Model (GAM) employing cubic regression splines for the log-distance to the city center, with parametric controls from Model (4) – the Simplified Perimeter Distances Model – as detailed in Table 1. This depiction includes comparisons with linear and second-degree polynomial models. The estimated implied teleportation threshold from Table 2 is also shown. Coefficients for parametric terms are provided in Table 4 in the Appendix. For figures related to alternative model specifications, refer to Figure 3 in the main text, or Figures 6 and 7 in the Appendix.

Parametric Coefficients from a Semi-Parametric Generalized Additive Model

	Dependent Variable: Log-Price (US Dollars)			
Covariates: Log-Distances (Meters) to	(1) Central Distances	(2) Perimeter Distances	(3) Central Distances (Simplified)	(4) Perimeter Distances (Simplified)
Northern Plaza	−1.025*	−0.518***		
	(0.546)	(0.098)		
North-Eastern Plaza	−1.661***	−0.546***		
	(0.215)	(0.082)		
Eastern Plaza	−1.750***	−0.475***		
	(0.167)	(0.059)		
South-Eastern Plaza	−1.958***	−0.577***		
	(0.154)	(0.047)		
Southern Plaza	−2.018***	−0.504***		
	(0.152)	(0.041)		
South-Western Plaza	−1.942***	−0.583***		
	(0.140)	(0.037)		
Western Plaza	−1.687***	−0.377***		
	(0.221)	(0.111)		
North-Western Plaza	−1.796***	−0.692***		
	(0.295)	(0.114)		
Closest Plaza			−0.855***	−0.396***
			(0.074)	(0.027)
Closest Street	−0.223***	−0.214***	−0.220***	−0.219***
	(0.014)	(0.014)	(0.013)	(0.013)
Closest Business District			−0.149***	−0.145***
			(0.020)	(0.020)
Closest Gaming District			−0.079***	−0.082***
			(0.019)	(0.018)
Closest Culture & Education District			0.011	0.009
			(0.013)	(0.013)
Closest Politics District			0.025	0.031*
			(0.017)	(0.017)
Constant	112.245***	37.691***	11.873***	8.879***
	(7.943)	(1.942)	(0.471)	(0.184)
Control: Log-Distances (Meters) to All 56 Individual Districts	Yes	Yes	No	No
Control: SW-NE-Diagonal-Dummy	Yes	Yes	Yes	Yes
Observations	34,358	34,358	34,358	34,358
Adjusted R^2	0.48	0.497	0.451	0.477

Table 4: Parametric coefficients from the semi-parametric Generalized Additive Model (GAM) with smoothing for the log-distance to the city center in Figures 3, 6, 7, and 8. Models (1) and (3) – the Central Distances Models – consider distances to the center of all plazas, while Models (2) and (4) – the Perimeter Distances Models – consider the distances to the closest parcel associated with a plaza. Models (3) and (4) use simpler model specifications where only the distances to the closest plaza and the distances to the closest district per category are considered. Models (1) and (2) control for the distances to all 56 districts individually. Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors in parentheses (Conley, 1999); * significant at 10%, ** significant at 5%, *** significant at 1%.

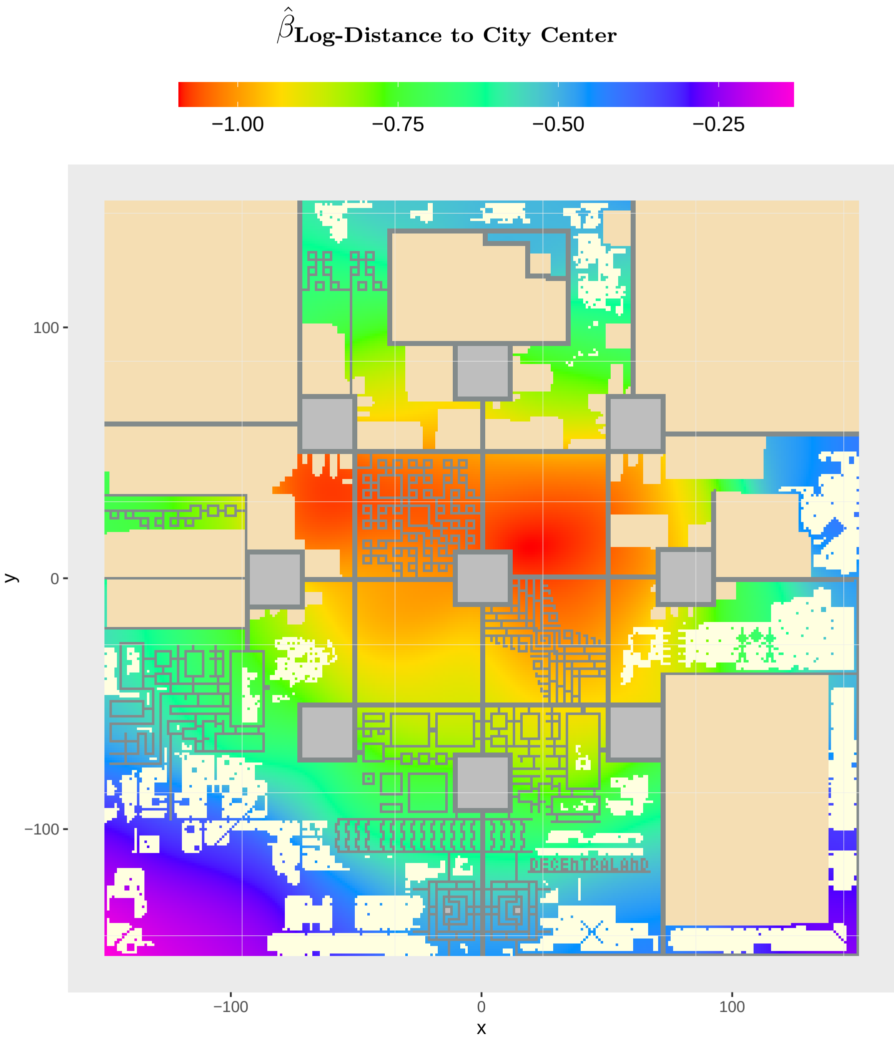

Figure 9: Locally Weighted Regression (LWR) (Cleveland, 1979) results for the estimated coefficients of the log-distance to the city center using Weighted Least Squares (WLS) with a Gaussian kernel utilizing a "leave one out"-validated bandwidth parameter of 130.38 meters. The other terms from Model (2) – the Perimeter Distances Model – in Table 1 enter parametrically as controls. Coefficients for parametric terms are provided in Table 5 in the Appendix. For figures related to alternative model specifications, refer to Figure 4 in the main text, or Figures 10 and 11 in the Appendix.

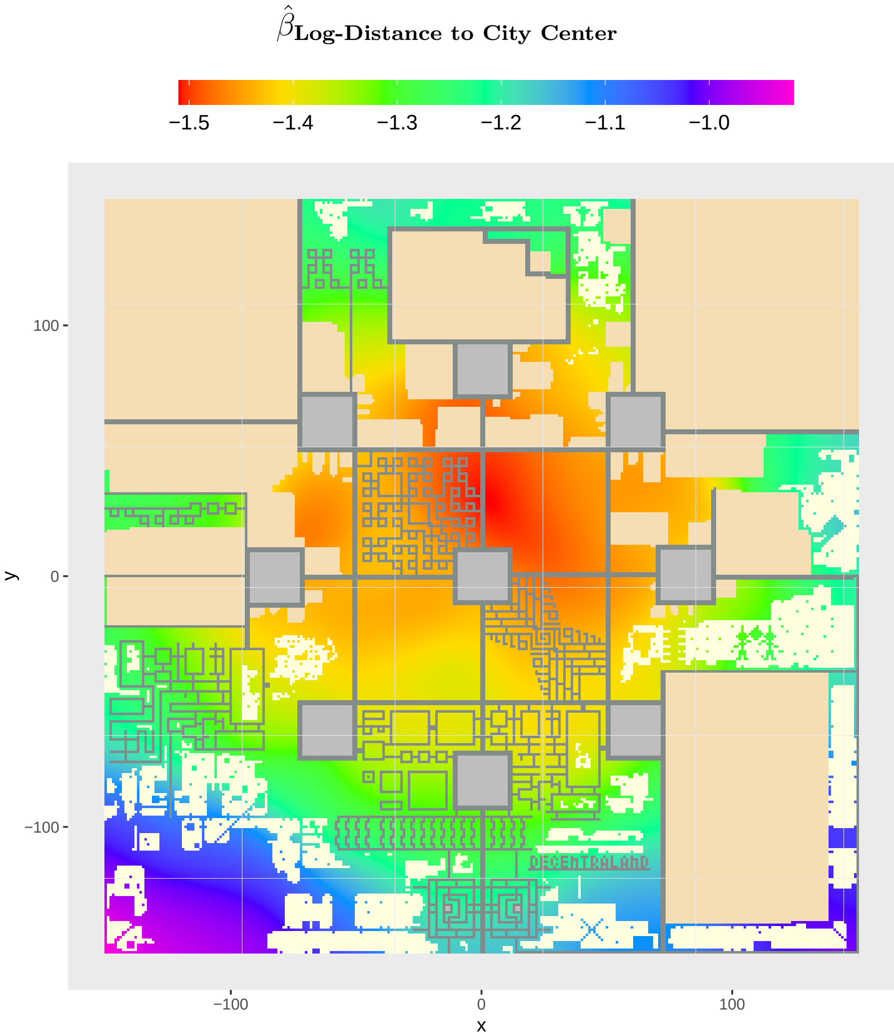

Figure 10: Locally Weighted Regression (LWR) (Cleveland, 1979) results for the estimated coefficients of the log-distance to the city center using Weighted Least Squares (WLS) with a Gaussian kernel utilizing a "leave one out"-validated bandwidth parameter of 130.38 meters. The other terms from Model (3) – the Simplified Central Distances Model – in Table 1 enter parametrically as controls. Coefficients for parametric terms are provided in Table 5 in the Appendix. For figures related to alternative model specifications, refer to Figure 4 in the main text, or Figures 9, and 11 in the Appendix.

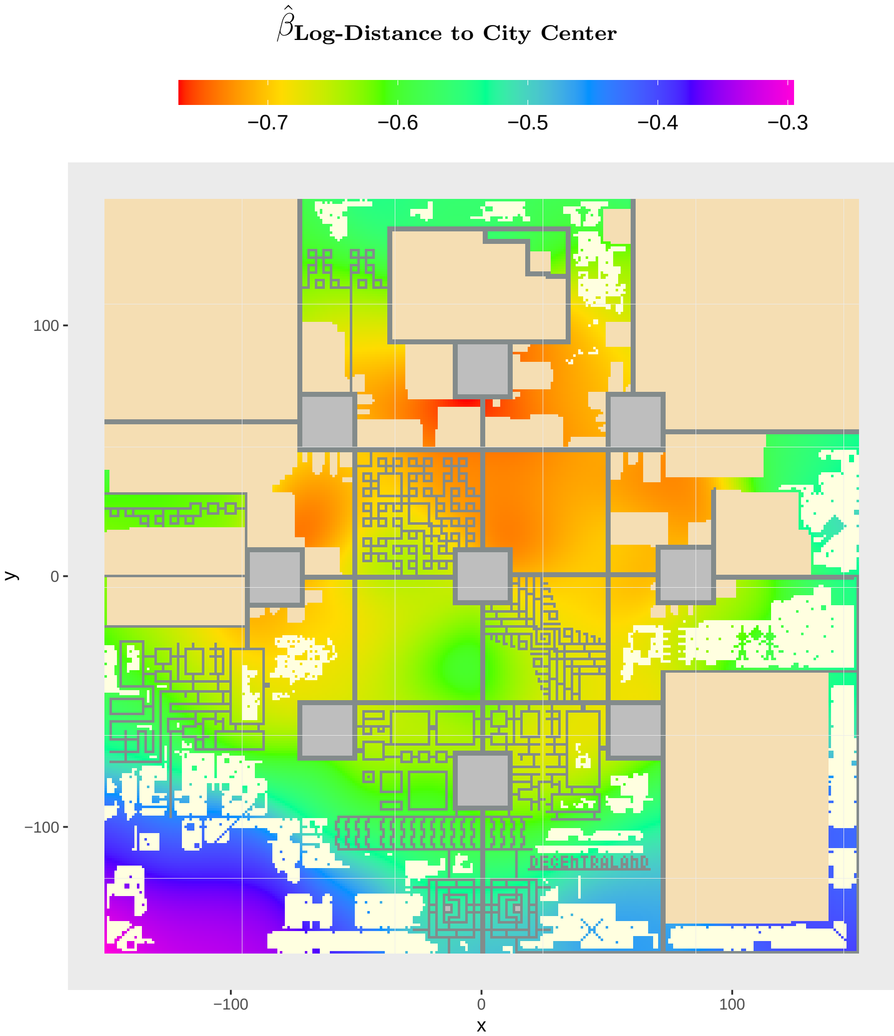

Figure 11: Locally Weighted Regression (LWR) (Cleveland, 1979) results for the estimated coefficients of the log-distance to the city center using Weighted Least Squares (WLS) with a Gaussian kernel utilizing a "leave one out"-validated bandwidth parameter of 130.38 meters. The other terms from Model (4) – the Simplified Perimeter Distances Model – in Table 1 enter parametrically as controls. Coefficients for parametric terms are provided in Table 5 in the Appendix. For figures related to alternative model specifications, refer to Figure 4 in the main text, Figures 9, and 10 in the Appendix.

Parametric Coefficients from a Semi-Parametric Locally Weighted Regression Model

	Dependent Variable: Log-Price (US Dollars)			
Covariates: Log-Distances (Meters) to	(1) Central Distances	(2) Perimeter Distances	(3) Central Distances (Simplified)	(4) Perimeter Distances (Simplified)
Northern Plaza	−0.147	−0.548***		
	(0.959)	(0.136)		
North-Eastern Plaza	−0.480	−0.655***		
	(0.491)	(0.165)		
Eastern Plaza	−0.144	−0.402***		
	(0.397)	(0.095)		
South-Eastern Plaza	−0.277	−0.454***		
	(0.322)	(0.082)		
Southern Plaza	−0.100	−0.243***		
	(0.289)	(0.078)		
South-Western Plaza	−0.117	−0.286***		
	(0.266)	(0.066)		
Western Plaza	0.811	−0.180		
	(0.658)	(0.231)		
North-Western Plaza	0.146	−0.631***		
	(0.608)	(0.206)		
Closest Plaza			−0.834***	−0.427***
			(0.089)	(0.031)
Closest Street	−0.313***	−0.332***	−0.309***	−0.323***
	(0.024)	(0.023)	(0.021)	(0.022)
Closest Business District			−0.354***	−0.354***
			(0.069)	(0.067)
Closest Gaming District			−0.079*	−0.090**
			(0.042)	(0.036)
Closest Culture & Education District			−0.023	−0.041
			(0.036)	(0.037)
Closest Politics District			−0.057	−0.070
			(0.048)	(0.048)
Constant	31.902***	38.993***	22.122***	14.767***
	(5.676)	(2.688)	(1.536)	(0.505)
Control: Log-Distances (Meters) to All 56 Individual Districts	Yes	Yes	No	No
Control: SW-NE-Diagonal-Dummy	Yes	Yes	Yes	Yes
Observations	34,358	34,358	34,358	34,358
Adjusted R^2	0.494	0.538	0.506	0.542

Table 5: Parametric coefficients from the semi-parametric Locally Weighted Regression (LWR) (Cleveland, 1979) model in Figures 4, 9, 10, and 11. The log-distance to the central plaza is spatially varying. Observations are weighed with Gaussian kernel utilizing a "leave one out"-validated bandwidth parameter of 130.38 meters. Models (1) and (3) – the Central Distances Models – consider distances to the center of all plazas, while Models (2) and (4) – the Perimeter Distances Models – consider the distances to the closest parcel associated with a plaza. Models (3) and (4) use simpler model specifications where only the distances to the closest plaza and the distances to the closest district per category are considered. Models (1) and (2) control for the distances to all 56 districts individually. Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors in parentheses (Conley, 1999); * significant at 10%, ** significant at 5%, *** significant at 1%.

Hedonic Regression Model Estimates with Investor-Specific Effects

	Dependent Variable: Log-Price (US Dollars)			
Covariates: Log-Distances (Meters) to	(1) Central Distances	(2) Perimeter Distances	(3) Central Distances (Simplified)	(4) Perimeter Distances (Simplified)
Central Plaza	−0.967***	−0.583***	−0.565***	−0.398***
	(0.092)	(0.044)	(0.050)	(0.030)
Northern Plaza	−0.024	−0.468***		
	(0.587)	(0.087)		
North-Eastern Plaza	0.195	−0.091		
	(0.164)	(0.072)		
Eastern Plaza	0.107	−0.057		
	(0.110)	(0.058)		
South-Eastern Plaza	0.245***	0.119***		
	(0.072)	(0.046)		
Southern Plaza	0.093	0.028		
	(0.061)	(0.035)		
South-Western Plaza	0.020	0.008		
	(0.057)	(0.034)		
Western Plaza	0.483***	0.056		
	(0.130)	(0.084)		
North-Western Plaza	0.178	−0.151		
	(0.181)	(0.095)		
Closest Plaza			−0.051	−0.109***
			(0.036)	(0.018)
Closest Street	−0.172***	−0.172***	−0.155***	−0.158***
	(0.012)	(0.013)	(0.011)	(0.011)
Closest Business District			−0.080***	−0.085***
			(0.016)	(0.015)
Closest Gaming District			−0.044***	−0.047***
			(0.014)	(0.013)
Closest Culture & Education District			0.052***	0.046***
			(0.013)	(0.013)
Closest Politics District			0.072***	0.082***
			(0.015)	(0.015)
Control: Investor-Specific Effects	Yes	Yes	Yes	Yes
Control: Log-Distances (Meters) to All 56 Individual Districts	Yes	Yes	No	No
Control: SW-NE-Diagonal-Dummy	Yes	Yes	Yes	Yes
Observations	34,358	34,358	34,358	34,358
Adjusted R^2	0.991	0.991	0.99	0.991

Table 6: Hedonic Regression Model estimates using Ordinary Least Squares (OLS). Models (1) and (3) – the Central Distances Models – consider distances to the center of all plazas, while Models (2) and (4) – the Perimeter Distances Models – consider the distances to the closest parcel associated with a plaza. Models (3) and (4) use simpler model specifications where only the distances to the closest plaza and the distances to the closest district per category are considered. Models (1) and (2) control for the distances to all 56 districts individually. All models utilize investor-specific effects based on the buyers' Ethereum addresses instead of a global intercept. Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors in parentheses (Conley, 1999); * significant at 10%, ** significant at 5%, *** significant at 1%.

Transformed Distances Model Estimates with Investor-Specific Effects

	Dependent Variable: Log-Price (US Dollars)			
Covariates: Log-Distances (Meters) to	(1) Central Distances	(2) Perimeter Distances	(3) Central Distances (Simplified)	(4) Perimeter Distances (Simplified)
Central Plaza	−3.762***	−1.440***	−1.600***	−0.654***
	(0.162)	(0.043)	(0.087)	(0.030)
Northern Plaza	−0.791***	−0.376***		
	(0.264)	(0.078)		
North-Eastern Plaza	−0.930***	−0.619***		
	(0.270)	(0.086)		
Eastern Plaza	−0.460**	−0.314***		
	(0.209)	(0.065)		
South-Eastern Plaza	−0.623***	−0.457***		
	(0.156)	(0.060)		
Southern Plaza	−0.866***	−0.364***		
	(0.113)	(0.039)		
South-Western Plaza	−0.808***	−0.419***		
	(0.108)	(0.033)		
Western Plaza	−0.355	−0.293***		
	(0.250)	(0.108)		
North-Western Plaza	−0.765**	−0.628***		
	(0.390)	(0.112)		
Closest Plaza			−0.356***	−0.197***
			(0.038)	(0.015)
Closest Street	−0.185***	−0.248***	−0.174***	−0.175***
	(0.011)	(0.013)	(0.010)	(0.010)
Closest Business District			−0.110***	−0.104***
			(0.015)	(0.015)
Closest Gaming District			−0.042***	−0.049***
			(0.015)	(0.014)
Closest Culture & Education District			0.036***	0.036***
			(0.011)	(0.011)
Closest Politics District			0.038***	0.055***
			(0.014)	(0.014)
Implied Teleportation Threshold (Meters)	275.401	114.567	462.883	453.8
Control: Investor-Specific Effects	Yes	Yes	Yes	Yes
Control: Log-Distances (Meters) to All 56 Individual Districts	Yes	Yes	No	No
Control: SW-NE-Diagonal-Dummy	Yes	Yes	Yes	Yes
Observations	34,358	34,358	34,358	34,358
Adjusted R^2	0.992	0.992	0.991	0.992

Table 7: Transformed distances model estimates with distance variables $min\{d_{im}, \bar{d}\}$ using Ordinary Least Squares (OLS). Models (1) and (3) – the Central Distances Models – consider distances to the center of all plazas, while Models (2) and (4) – the Perimeter Distances Models – consider the distances to the closest parcel associated with a plaza. Models (3) and (4) use simpler model specifications where only the distances to the closest plaza and the distances to the closest district per category are considered. Models (1) and (2) control for the distances to all 56 districts individually. All models utilize investor-specific effects based on the buyers' Ethereum addresses instead of a global intercept. Implied teleportation thresholds are estimates from Table 2. Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors in parentheses (Conley, 1999); * significant at 10%, ** significant at 5%, *** significant at 1%.