Monetary Metanomics: The Effect of Monetary Policy on Virtual Real Estate Prices*

Moritz Grebe † Salah Hassanin ‡

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Abstract

This paper examines the impact of monetary policy on virtual real estate prices within the Decentraland metaverse. Utilizing transaction data from various blockchain marketplaces and metadata from parcel sales, we construct a daily Decentraland Price Index (DPI) based on a hedonic price model. Using state-dependent local projections, we show how the effect of the Federal Reserve's monetary policy varies with levels of user activity. We find that in high user-activity states, a monetary policy shock of 25 basis points leads to an immediate 20% decrease in the DPI, with the effect peaking at 45% by the fourth day. Our results not only demonstrate the sensitivity of virtual real estate markets to changes in monetary policy but also highlight the economic parallels between virtual and physical real estate. Understanding these dynamics is essential for managing risks and capitalizing on opportunities within this emerging digital economy.

Keywords: metaverse, Decentraland, virtual real estate, hedonic price index, monetary policy, price dynamics, user activity, blockchain data
JEL Classification: E52, R31 , G12

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†Justus-Liebig-University Gießen, Germany, Email: moritz.grebe@wirtschaft.uni-giessen.de

‡Justus-Liebig-University Gießen, Germany, Email: salah.hassanin@wirtschaft.uni-giessen.de

1 Introduction

The concept of a metaverse existed before Facebook's rebranding to Meta popularized it, yet this event marked the beginning of a significant surge in interest and adoption. The metaverse is a vast interconnected network of 3D virtual worlds designed for synchronous, persistent experiences by countless users (Ball, 2022). As one of the largest metaverse platforms, Decentraland exemplifies this paradigm. Powered by the Ethereum blockchain, Decentraland is a pioneering metaverse platform that amalgamates the principles of decentralization and virtual reality (Ordano et al., 2024). In alignment with the mentioned metaverse features in Dwivedi et al. (2022) and Park and Kim (2022), users can interact through avatars in social activities, attend community-driven events, engage in gaming, pursue 3D-based learning, and create and monetize content. This environment emphasizes user governance and ownership, blurring the lines between physical and digital realms and introducing novel economic dynamics.

Although the initial hype has subsided, the metaverse's significant future potential remains a subject of rigorous academic scrutiny. Specifically, very little is known about the economics of metaverses (Goldberg et al., 2024), termed metanomics, and even less about its relationship with the real-world economy.

In this paper, we therefore examine the effect of monetary policy on prices in the metaverse. More specifically, we look at the prices of virtual real estate in Decentraland. These prices have an important characteristic that distinguishes them from many other virtual assets and makes them comparable to their real-world counterparts: they can not only be bought and sold, but also rented to users. If we understand the price of a property as the sum of all present values of future rental payments, then monetary policy could influence prices via the discount rate. An unexpected rise in interest rates would then lead to a fall in prices, as would be expected in the real world.

To test this, we first need information about Decentraland's virtual land, such as prices and location. This virtual world comprises $90,601$ land parcels,

approximately 40,000 of which are privately owned. Owners of private parcels can modify their content, merge them with other parcels, rent them out, or offer the parcel for sale. The open architecture of the underlying blockchain offers a transparent dataset of virtual land information. Every economic activity is recorded on the blockchain and consequently can be tracked.

We therefore collect relevant on-chain transaction data for parcel sales and transfers in Decentraland from its marketplace, various other blockchain marketplaces (OpenSea, X2Y2, etc.), and cross-reference it with data aggregation services like Reservoir to ensure data integrity. This dataset includes detailed information on buyers, sellers, daily sales prices, transaction dates, and unique parcel identifiers. Additionally, we gather metadata for each parcel, such as coordinates, adjacency to roads and districts, and whether the coordinates are easy to remember. Combining all successful sales into our dataset, we end up with 24,237 successful sales transactions between March 20, 2018, and September 20, 2023. The average transaction price is \$7,207.46, with the highest reaching \$405,406.40.

We then use these transactions to calculate the daily Decentraland Price Index (DPI), based on the hedonic price index model methodology used for the German Real Estate Index (Osswald do Amaral et al., 2023). This approach is particularly suited for this analysis as it allows us to decompose the price of virtual land into constituent attributes that affect its value, such as location within the virtual world, proximity to roads and plazas, ease of remembering parcel coordinates, and adjacency to prominent districts. This enables us to isolate the effect of each characteristic on land prices, ensuring that our analysis accurately reflects the value drivers in this unique market and estimate a quality-adjusted price index.

To estimate the effect of monetary policy, we update the time series of Fed monetary policy surprises from Bu et al. (2021) and employ local projections (Jordà, 2005). We observe a negative effect on prices: after a monetary policy shock of 25 basis points, the DPI falls by approximately 20%. However, this substantial effect is only statistically significant on the fourth day following the shock.

User activity on Decentraland has seen notable fluctuations since its inception. Initially, the platform was relatively unknown, with only a few users interacting and trading land parcels. During the height of its popularity, both user numbers and transaction volumes surged significantly, only to decline once the hype subsided. We argue that the level of user activity—whether high or low—impacts market dynamics. One might expect that the more users engage with Decentraland, the more prices should react as in the real world. However, if user activity is low and the majority of users are high-risk investors accustomed to investing in virtual assets, the effect is less clear.

We use state-dependent local projections and identify states with high and low user activity using the approach of Born et al. (2020): we use a variable from our transaction data set as state variable: the number of sales transactions per day and, on the other hand, the number of active user wallet addresses per day that we download from Messari.[1]

The results are very similar for both specifications: in the state with high user activity prices fall by 15% on the day of the shock. The largest drop occurs on day three, with around 45%. After day 4 the effect gets insignificant. In the state with low activity, we see a positive effect on the first and second day after the shock.

We can thus show that the prices of virtual land in Decentraland actually respond to the Fed's monetary policy. An unexpected rise in interest rates leads to a sharp but very short-lived decline in prices. This effect is particularly pronounced when user activity is high.

Our paper contributes to different strands of the literature. First, our paper adds to the literature by advancing the understanding of economic principles governing virtual real estate markets, particularly within metaverse platforms like Decentraland. Recent research on virtual real estate in the metaverse has yielded several important insights relevant to pricing and economic dynamics within these platforms. Studies indicate that virtual land prices often display inefficiencies and high volatility. Yet, they have shown a consistent upward trend, driven by speculative behavior and the unique characteristics of NFTs (Dowling (2022a), Dowling (2022b)). There is also

[1] https://messari.io/project/decentraland

evidence of limited but significant co-movement between virtual land prices and cryptocurrency markets, particularly with Ether, highlighting a potential link between these digital asset classes (Dowling (2022b), Nakavachara and Saengchote (2022)). The value of virtual land is further influenced by location, similar to physical real estate, where proximity to key virtual landmarks significantly affects prices (Goldberg et al. (2024), Güven and Ercan (2022)). Additionally, the medium of exchange used, such as cryptocurrency versus fiat currency, can impact the willingness to pay for virtual land, suggesting that monetary policies could influence these emerging digital markets (Nakavachara and Saengchote (2022), Yencha (2023)). These findings underscore the need for a nuanced understanding of virtual real estate, particularly as it relates to broader economic and monetary policy considerations in digital economies. Second, we contribute to the literature investigating the relationship between monetary policy and asset prices. House prices, in particular, are seen as key elements of the business cycle. Especially since the house price boom and the subsequent financial crisis, understanding the interaction between monetary policy and house prices has become increasingly important (Del Negro and Otrok (2007), Iacoviello (2005)). Jordà et al. (2015) find a crucial role of loose monetary policy in house price booms and argue, just like Kiley (2021), that house price dynamics can be predictive of crises.

Overall, it seems that monetary policy has a large effect on house prices. For instance, Benati (2021) find a negative effect of a positive monetary policy shock on real house prices that is three to five times larger than the effect on real GDP. Furthermore, the effects seem persistent, and prices do not react on impact but usually only after about a year (see Goodhart and Hofmann (2008), Williams (2015), Hülsewig and Rottmann (2021) or Xie (2024)). Xie (2024) attributes this "sluggishness" to the information channel, arguing that households are not informed about current changes in monetary policy and only become aware of them much later through news about changes in house prices.

The reaction of house prices, however, is heterogeneous across the countries considered, and seems to depend on the mortgage markets. Calza et al.

(2013) and Benati (2021) find that house prices react more strongly when mortgage markets are more developed and flexible. Paul (2020) finds that the effects are stronger when house prices are high and less strong when they are low.

Later, we will discuss the differences between all of these findings and our results on virtual real estate.

This paper is structured to first provide an overview of Decentraland and its virtual real estate market, followed by the methodology used to construct the Decentraland Price Index (DPI) from on-chain transaction data. It then analyzes the effects of Federal Reserve monetary policy shocks on virtual real estate prices using state-dependent local projections, with a focus on user activity. The paper concludes with a discussion of the findings' implications for stakeholders in the metaverse and robustness checks to validate the results.

2 Decentraland

Decentraland, launched as beta and raised more than $24 million in its initial coin offering (ICO) in 2017 (ICO Drops (2017)) and opened to the public in 2020 (Decentraland (2020)), is a pioneering metaverse platform that amalgamates the principles of decentralization and virtual reality, powered by the Ethereum (ETH) blockchain. Ball's (2022) metaverse definition of the metaverse applies to Decentraland: Decentraland is a vast interconnected network of 3D virtual worlds designed for synchronous, persistent experiences by countless users. In alignment with the mentioned metaverse features in Dwivedi et al. (2022) and Park and Kim (2022), users can engage through their avatars in social activities, attend community-driven events, play games, educate themselves, explore the virtual world, and create, experience, and monetize content (e.g., avatar fashion and art) and applications (e.g., gambling) in a 3D immersive environment. By extending the social significance, the metaverse integrates with the real world (Park and Kim, 2022). Moreover, Decentraland expands human activities by transcending the natural limitations of space, time, and resources, a characteristic of the metaverse described by Momtaz (2022).

Inspired by Web 3.0, The metaverse Decentraland operates within a decentralized metaverse model. The decentralized metaverse model represents a paradigm shift towards a model where control and ownership are distributed among its users rather than being held by a single entity (Cantú et al. (2024)). This virtual world is built on blockchain technology, utilizing fungible tokens (digital currency), non-fungible tokens (NFTs), and DAO, which empower users to govern without a centralized authority. These technologies collectively enable an open, interoperable, and user-governable digital universe (Huynh-The et al. (2023), Despotović et al. (2023), Goldberg and Schär (2023)). Consequently, users in Decentraland have complete control over the land they own, the assets they create, and their transactions, contributing to an ecosystem where they are major stakeholders and beneficiaries. Additionally, they support a personal sense of presence and maintain data continuity across identity, history, entitlements, objects, communications, and payments. This model not only overcomes the limitations of centralized systems, such as lack of trust and potential censorship (Goldberg and Schär (2023)), but also fosters the creation of virtual environments that are equitable, secure, and user-driven. The decentralized model places the responsibility of privacy and security on the individual users, lacking a centralized body to address issues like abuse or enforce policies. It places the responsibility of privacy and security on individual users, as there is no centralized body to address issues like abuse or enforce policies, thereby laying the foundation for an open digital economy. Consequently, fungible and non-fungible tokens (NFTs) play a crucial role in this virtual world by representing Decentraland's currency, MANA, and a variety of virtual assets. MANA follows like ETH the Ethereum Request for Comments 20 (ERC-20) standard, allowing for standardized transactions and economic activities. ERC-20 tokens are identical and can be exchanged on a one-to-one basis. NFTs include unique land parcels (LAND), estates, wearable items for avatars, unique avatar names, and digital art and collectibles, all of which can be bought, sold, or traded on Decentraland's marketplace or alternative marketplaces, such as OpenSea. In the Ethereum blockchain, NFTs follow the ERC-721 standard. They are distinctive assets, each with unique identi-

fication codes and metadata that set them apart. They cannot be replicated or divided like ERC-20 tokens. This uniqueness allows NFTs to represent ownership or proof of authenticity.

Alongside the decentralized metaverse The Sandbox (The Sandbox, 2020), Decentraland (Ordano et al., 2024) represent the forefront of integrating virtual economies with blockchain technology. The two most powerful platforms utilize their MANA and SAND tokens for transactions and governance. These platforms offer unique digital asset experiences, like virtual land (LAND), and empower user participation in platform evolution via DAOs. Both platforms have garnered attention from major brands (The Sandbox (2024), Decentraland (2023), Decentraland Fandom (2024)) and celebrities (Hazan et al. (2022)), underscoring the real-world relevance of virtual economies. In these worlds, LAND scarcity mirrors the physical world. It ensures no risk of dilution by central authorities and safeguards against unilateral rule changes that could disrupt the ecosystem. Among all NFTs, LAND is not merely a digital asset but a foundation for diverse creative and social endeavors. Their open architecture offers a transparent dataset of – among other things – LAND prices, which makes these metaverses a perfect setting for observable experiments with real monetary stakes. Moreover, both platforms' parcel size and shape uniformity facilitate comparability and consistency in the virtual real estate market. Compared to The Sandbox, Decentraland stands out for its symmetrical geographic layout (more in chapter x.y), where the parcels are embedded in a strict grid structure. Moreover, as the pioneering major blockchain-based virtual world, Decentraland potentially provides a richer repository of historical data, offering more profound insights into digital land economics. Furthermore, Decentraland's focus on a wide array of virtual experiences, including art, events, and fashion - beyond gaming - (Ordano et al., 2024; The Sandbox, 2020) paired with lower transaction fees (2.5% Vs. 5%; Chanda, 2023), positions it as a particularly appealing environment for creators and investors. Given its pioneering status, a wealth of historical data, and a broad spectrum of virtual experiences coupled with economic incentives, Decentraland emerges as the primary focus of our research, promising unique insights into the dynamics of virtual

real estate within decentralized metaverses.

From the economic lens, Decentraland embodies, like The Sandbox (Nakavachara and Saengchote, 2022), an open economy characterized by the absence of capital control and monetary sovereignty, and a fully flexible exchange rate, according to the Impossible Trinity (Dornbusch, 1976). This is facilitated by the unrestricted convertibility of blockchain tokens that ensures perfect capital mobility, the completely decentralized financial system (DeFi), and the easy virtual economy's currency exchange by other currencies. The platform's emphasis on DAO for governance and property rights (LAND ownership) introduces a novel dimension to virtual real estate. This invites an analysis of how decentralized environments might reflect or diverge from traditional real estate markets under varying monetary policies and economic conditions.

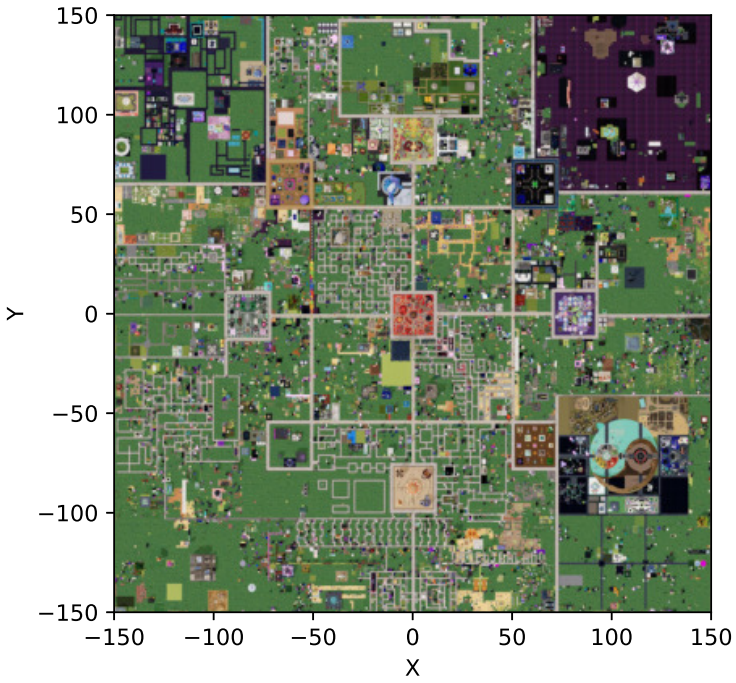
The rest of the chapter describes the collected Decentraland data and is accompanied by descriptive statistics and facts. Based on this data, the construction of a hedonic real estate price index and the monetary policy analysis will follow.

2.1 LAND Data

The parcels on the square-shaped Decentraland map are described two-dimensionally by x- and y-coordinates. Decentraland's basis consists of a central plaza with eight surrounding plazas, all equidistant in a circular pattern (see figure 1). The symmetrically structured metaverse consists of 90,601 parcels ($x, y \in [-150; 150]$), comprising 43,689 private parcels, 33,886 parcels within 39 DAO-approved community-built districts, 9,438 road parcels, and 3,588 parcels divided over nine plazas. All parcel sizes are standardized and are 256 square meters (16m x 16m). The owner of a parcel can modify its content (e.g., create a scene or build a house) and merge it with other neighboring parcels to form an estate (and vice versa). In addition, the owner can transfer the parcel to other users, give other users parcel editing rights, name the parcel, and give the parcel a public description.

We collected on-chain Decentraland parcel transaction data from various

Figure 1: Decentraland Map



Notes: Decentraland at a glance

marketplaces, covering the period from March 2018 to August 2023[2], and cross-checked it with Reservoir's data aggregation service for integrity. Afterward, the datasets of the various marketplaces were filtered. For example, some marketplaces only show successful transactions, while others also show failed transactions.[3] As the various marketplaces use, for example, different

[2]The lack of on-chain Decentraland LAND parcel transaction data before March 2018 is because the Terraform Event, which took place from December 2017 to January 2018, involved off-chain bidding, with the actual on-chain registration and transfer of LAND ownership occurring later. The Decentraland LAND smart contracts were deployed in March 2018, marking the beginning of on-chain transactions. Therefore, on-chain data only became available after the contracts were live and LAND parcels were officially registered on the blockchain. The Decentraland Marketplace was released allowing users to buy and sell parcels (LAND) as well as explore the map.

[3]Failure may be due to fraud attempts, suspicious activity, or insufficient liquidity. A common reason for a failed transaction is gas. A fee (gas) is due for carrying out a transaction on the Ethereum blockchain, which depends on the network demand and

terminology for sellers (e.g., *sender*), buyers (e.g., *recipient*), closing time (e.g., *end time*) of a transaction, the datasets are harmonized to achieve consistency. Then, we concatenated and filtered the dataset as we only considered sales for the methodology application. Since transaction payments are accepted in various cryptocurrencies (e.g., Bitcoin and Ethereum) beyond the Decentraland marketplace (MANA), we have standardized all transactions by converting them to daily USD sales prices for consistency and later analysis. Out-of-market trust-based sales[4] are not and cannot be recorded. They only result in a transfer. However, a transfer can also be a gift or part of an exchange transaction. The final transaction dataset contains the daily USD sales prices, the closing dates (Central Standard Time), and the unique token ID with which the LAND NFTs can be identified. This allows us to add data on the parcels, such as the x-y-coordinates, direct access to roads, distance to a plaza, and others to describe and understand the value of a given parcel.

2.2 LAND Ownership

Transaction data offers a clear view of LAND activity within Decentraland, but examining the distribution of ownership provides a deeper understanding of the platform's evolving landscape. The decentralization of LAND ownership is a key factor in determining the inclusivity and sustainability of Decentraland's virtual ecosystem. The pattern of LAND ownership not only reveals the degree of decentralization but also highlights the shifts in control and accessibility within the marketplace. This study calculated the

transaction complexity. Accordingly, gas varies from the submission of a bid/purchase to the completion of the transaction. Thus, the buyer's cash balance may be insufficient to carry out the transaction if the gas fee increases unexpectedly during the transaction process. The gas fees are payouts to Proof-of-Work miners (pre-Merge) / Proof-of-Stake validators (post-Merge) on the ETH protocol who support and secure the ETH network. Therefore, gas has an activity-regulating function and maintains the network security and functionality in the ETH blockchain.

[4]Out-of-market trust-based sales refer to sales that occur outside established marketplaces, relying on trust between the parties involved rather than on the security and protocols of the marketplace. They depend on personal agreements, trust, or reputation of the parties to ensure that the terms of the sale are honored. Therefore, the transaction parties save on marketplace fees but bear the risk of fraud.

Gini coefficient G (Gini, 1912) over time to examine the distribution of land ownership in Decentraland's virtual real estate market, specifically assessing the decentralization development of LAND ownership:

$$G = \frac{1}{n}\left(\frac{\sum_{i=1}^{n}(2i - n - 1)\cdot x_i}{\sum_{i=1}^{n} x_i}\right)$$

In the Gini coefficient calculation, n represents the total number of participants, x_i denotes the number of LAND parcels owned by the i-th participant in the sorted list, and i is the index position of each participant in the sorted list of LAND owners. We determined the Gini coefficient on a monthly period. A G close to 0 (1) would indicate that LAND parcels are distributed relatively (un)equally among participants.

The Gini coefficient shows a long-term downward trend with two sharp drops (see figure 2). At the publication of Decentraland and public access to parcel trade, the coefficient falls from around 94% to 83%, and at the end of 2021, when trading activity has increased enormously. This indicates a redistribution of parcels of land across more landowners. Large landowners own fewer parcels. This finding is underpinned by other indicators. In the beginning, the top 5% (top 1%) owned almost 90% (82%) of the parcels, while in 2023, 66% (53%) of the parcels are still owned by them after the drastic drop at the time of publication, and the short-term sharp increase in trading activity (see figure 3). The Gini index rose briefly during the period of high market activity, but then returned to the same level and fell even further. This could be due to the active land purchases of the top 5% (1%) largest landowners who sold their land after the peak phase. Over the entire period, the average number of parcels per landowner has fallen from around 38 to 4 (-89.47%), and the number of different LAND owners has risen from 2,059 to 6,595 (+220.30%) (see figure 4). The number of properties in circulation has remained roughly the same after the drastic increase from around 12,800 to 65,000 from the launch of Decentraland until the end of the data set time horizon. At the end of the observed time window, the Gini coefficient remains at 70.71%. Compared to other virtual worlds, such as The Sandbox (77% in November 2022; Blockchain Research Lab (2022)), the LAND

parcels are less unevenly distributed. Compared to the real world, G lies between the USA (75%) and Germany (68%) (UBS, 2024)[5]. Overall, there has been a continuous long-term progression in decentralizing Decentraland LAND ownership. These changes indicate a significant move towards a more equitable distribution of virtual land, promoting greater accessibility and participation within Decentraland's virtual economy. This shift suggests a maturing market where land ownership is democratizing, potentially leading to a more stable and sustainable virtual real estate ecosystem.

2.3 Internal Factors influencing LAND Prices

In the context of Decentraland, several key factors significantly influence land prices. Understanding these dynamics is essential for making informed decisions within the virtual real estate market, particularly in the light of monetary policy impacts. We explore the spatial distribution of average LAND parcel prices in Decentraland at a descriptive level and compare our findings about the factors affecting land valuations to existing literature on the metaverse and the real world. Analyzing the heatmap (see figure 9), several patterns emerge:

- *Centrality*: Parcels located near the center of Decentraland (around 0, 0) command higher prices. This central region includes Genesis Plaza, a major hub known for high user traffic, significant landmarks and the starting point for users in Decentraland. The peripheral regions of Decentraland generally exhibit lower average sale prices. These areas tend to have fewer attractions or be less developed, leading to reduced demand. Central locations are more desirable due to their accessibility and visibility.

[5]It is important to note that the Gini coefficients for the USA and Germany in UBS (2024) reflect the distribution of wealth assets, which encompass a broader range of items beyond land alone. While this comparison is not perfectly aligned, it serves as a useful point of reference for understanding the relative inequality in virtual and real-world contexts, given the lack of more directly comparable data. In literature, one directly comparable but outdated source is Deininger and Olinto (2000): Germany Land Gini was at 55.39% and USA 73.10%.

- *Nearby Landmarks*: Proximity to notable landmarks and attractions, such as Fashion Street, District X (formerly known as Red Light District), Vegas City, Decentraland University, and the Conference Center, enhances parcel value. These areas are vibrant with activities, drawing consistent user engagement and visitors.

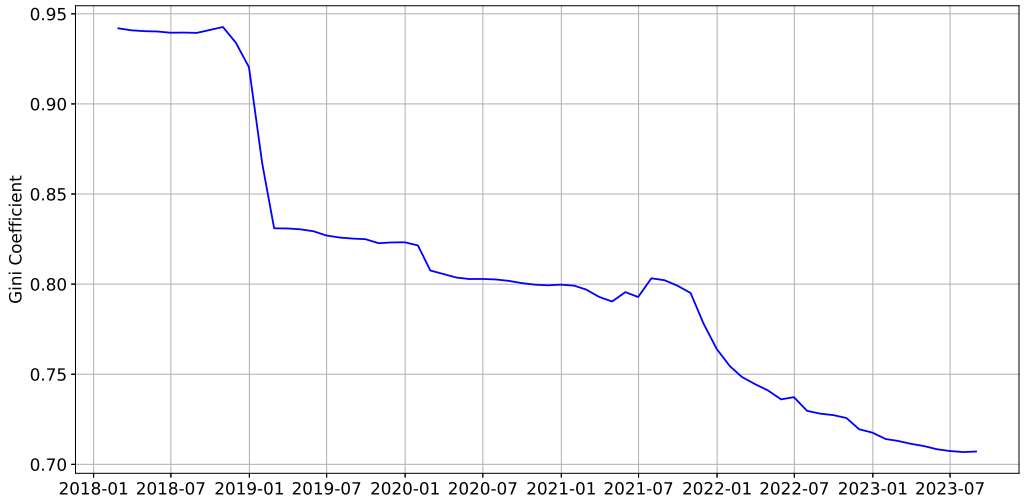
- *Community Projects*: The presence of community-driven projects like the AETHERIAN Project and themed areas such as Dragon Kingdom and Dragon City contribute to higher land values due to their active community involvement and themed events.

- *Roads and Plazas*: Parcels adjacent to major roads and plazas often show higher values. Good connectivity enhances accessibility, making these locations more attractive for development and user visits. Roads and plazas serve as critical infrastructure that improves navigation within Decentraland.

Overall, the spatial distribution of property prices in Decentraland indicates that location, proximity to key amenities, connectivity, and accessibility are influential factors. This insight aligns with previous literature on both virtual worlds (Goldberg et al., 2024) and the real world (Heikkila et al., 1989; Tyrväinen and Miettinen, 2000). For example, Heikkila et al. (1989) demonstrated that residential land values in polycentric urban areas like Los Angeles are significantly influenced by multiple subcenters rather than just the central business districts. Similarly, Tyrväinen and Miettinen (2000) found that proximity to forested areas and having forest views significantly increase property values. However, in Decentraland, the ability to walk or teleport between locations reduces the traditional significance of physical proximity to transport hubs (Bowes and Ihlanfeldt, 2001). Instead, the location value is more closely related to expected visitor density and the potential for random encounters (Goldberg et al., 2024). Consequently, calculations of land prices in Decentraland should focus on the virtual environment's attributes and strategic positioning relative to popular and high-traffic areas, rather than conventional proximity-distance relationships. Therefore, areas hosting

regular events, community gatherings, or collaborative projects may boost (nearby) parcel values. Active community involvement and engagement drive up demand and prices as they attract more visitors and participants. This shift in locational preferences reflects the unique dynamics of virtual worlds, where connectivity and accessibility take on new meanings. Finally, Decentraland's map infrastructure is polycentric. It is characterized by multiple centers of activity, decentralized ownership, and community-driven development, making it a vibrant and diverse virtual world.

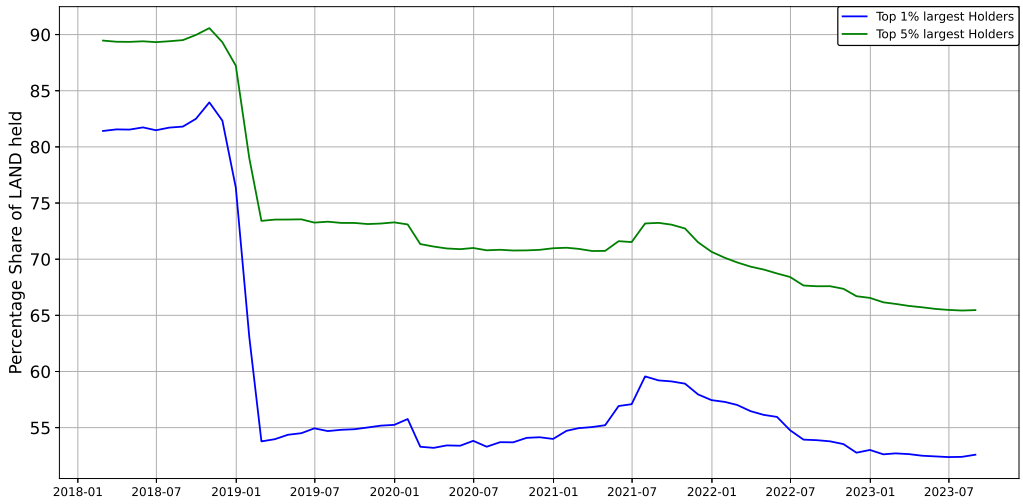
Figure 2: Gini Coefficient



2.4 LAND Market Activity

Market dynamics in the digital land sector reveal significant fluctuations driven by varying levels of activity, influencing both demand and pricing trends over time. The increasing activity and thus the potential demand for parcels, while the number of available parcels remains constant (see figure 5), leads to greater spikes in LAND prices in times of high activity (see figure 6 & 7). At times of low activity, such as 05/2019-01/2020, the average trading price of a LAND parcel is approx. $1022.82, the trading volume is approx. $0.12 million (see figure 8), and the successful transaction count is

Figure 3: Monthly LAND Ownership among the largest LAND Owners



Notes: The LAND distribution across the top 1% and 5% largest LAND owners.

159. Compared to the time frame (03/2021-08/2022), where activity peaks, several differences exist in the magnitude of several indicators. At the peak, the average trading price of a property is $17928.78 (+1652.88%), the trading volume is $32.92m (+27333.33%), and the number of transactions is 1910 (+1101.26%). The number of parcel owners during this period increased by 70.23% (from 3641 to 6198). This was followed by a decline in market activity to the previous level. Meanwhile, the decentralization indicators continued to show a steady increase, albeit very slow, such as in the LAND ownership of the top 5% (1%) largest LAND owners. In conclusion, the significant fluctuations in trading prices and volumes during peak periods underscore the speculative nature of this market, while the overall trend towards greater decentralization suggests a gradual stabilization as the user base continues to grow and diversify.

Figure 4: Monthly Number of LAND Owners & Average LAND Holdings

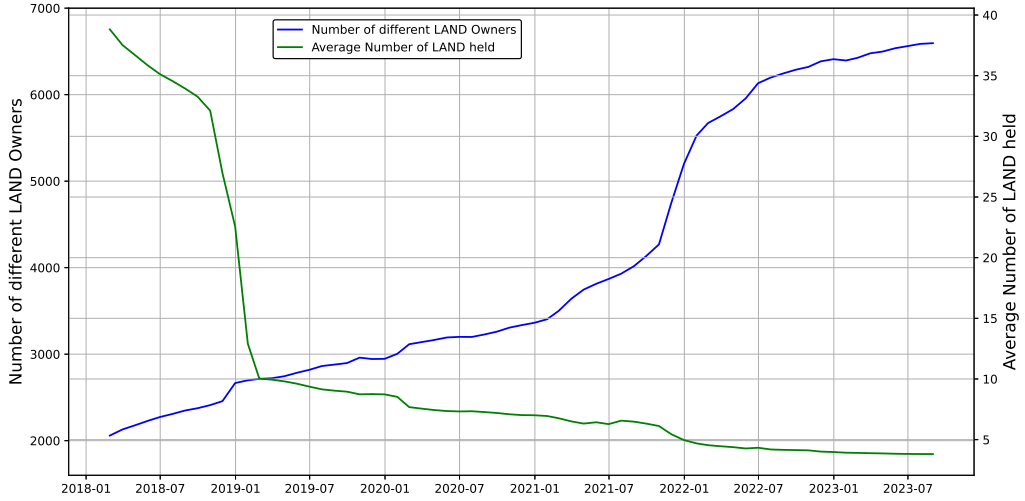


Figure 5: Monthly Circulating LAND

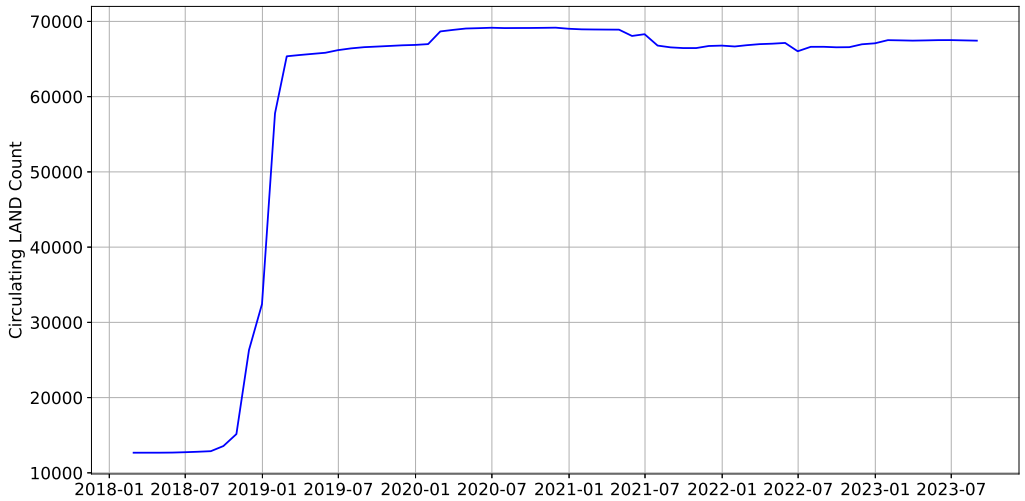


Figure 6: Average LAND Price

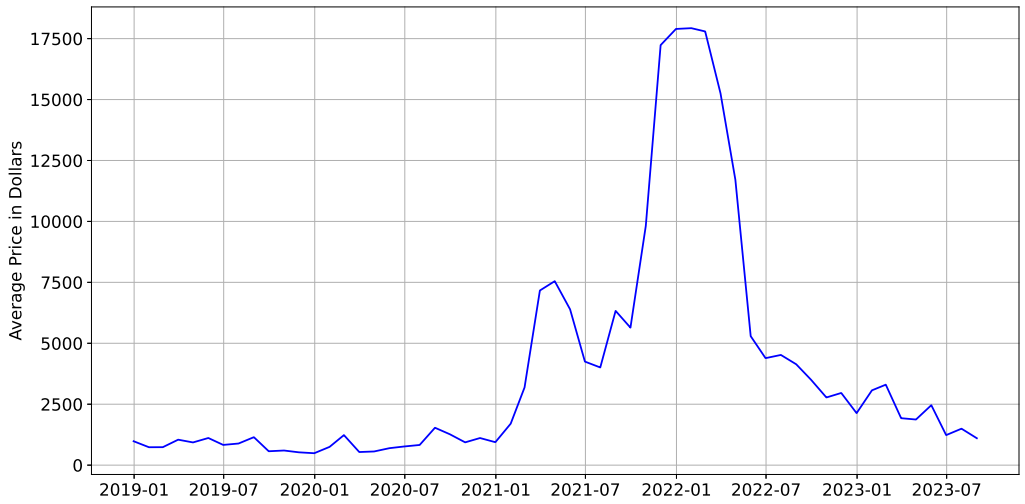
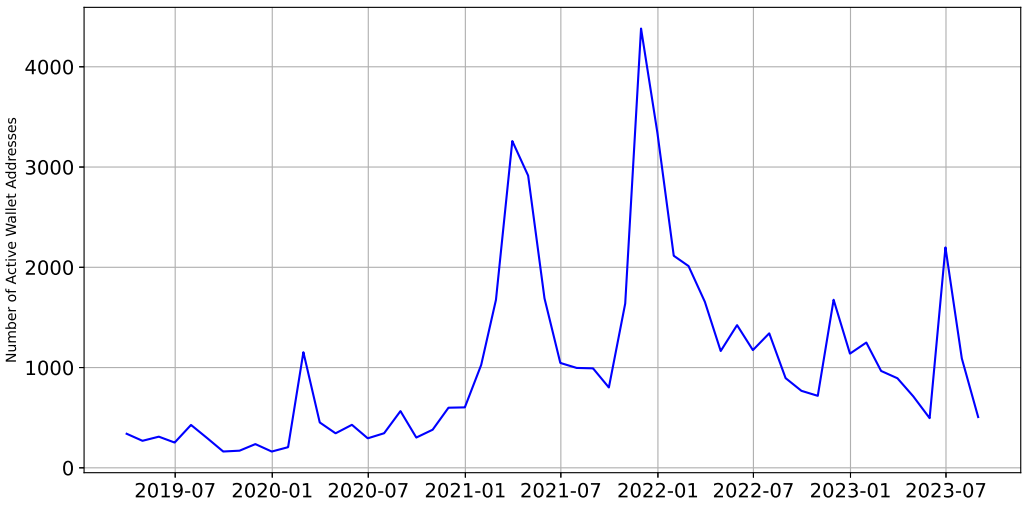
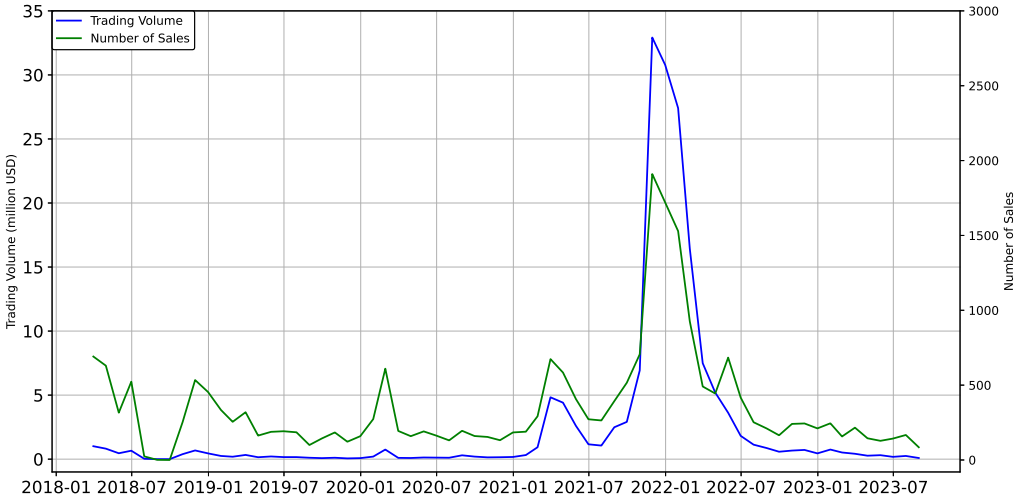


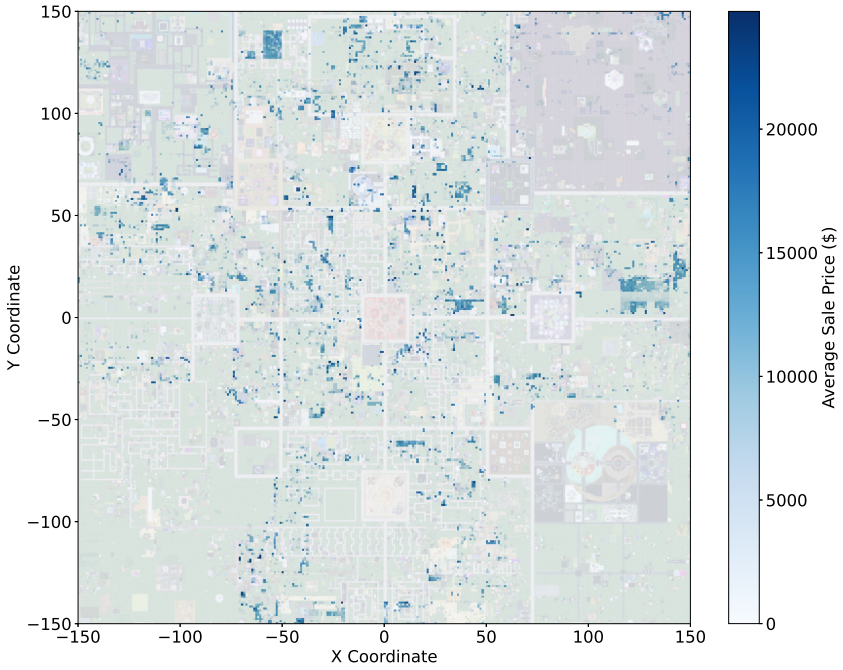
Figure 7: Number of Active Wallets



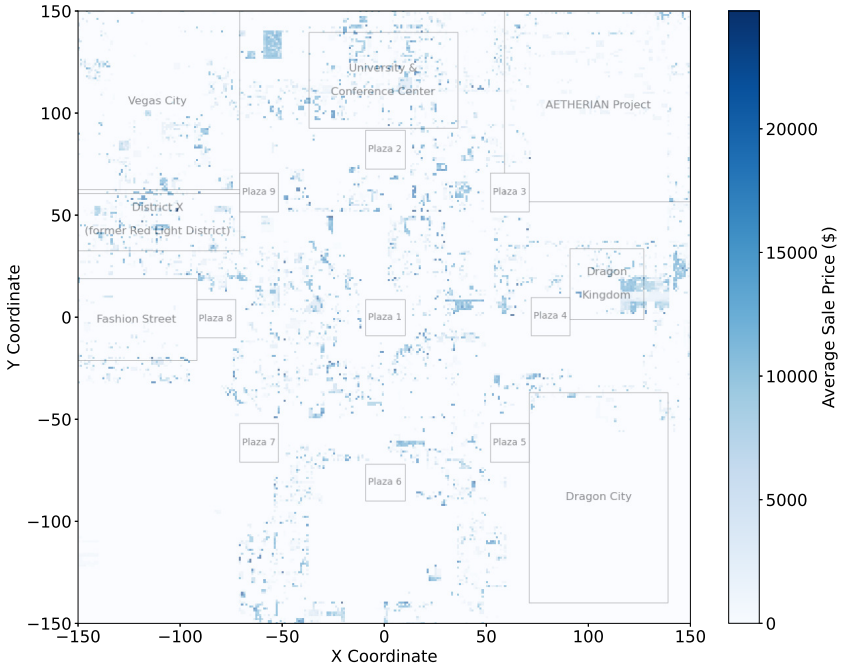
Notes: Monthly active Wallets in Decentraland

Figure 8: LAND Parcel Market Volume and Sales





(a) Decentraland background



(b) POI background

Figure 9: Decentraland Heatmap of average LAND parcel prices

3 The Decentraland Price Index

Given our database of successful sales transactions, we aim to construct a Decentraland price index. Simply averaging prices on a daily basis would not be an effective approach because parcels are not only sold infrequently, but also vary in their characteristics and consequently in their values. For example, on days with few transactions, the sale of a high-value parcel could skew the daily average and not accurately reflect the true price level. Therefore, average prices must be quality-adjusted. Following the method used to construct the German Real Estate Index (Osswald do Amaral et al., 2023), we use a time-dummy hedonic regression.[6]

We construct the Decentraland price index (DPI) as follows:

$$\ln p_{i,n}^{t} = \alpha + \sum_{\tau=1}^{T} \beta^{\tau} D_i^{\tau} + \sum_{k=1}^{K} \gamma^{k} z_n^{k} + \epsilon_t \tag{1}$$

For each transaction i, where a parcel n was sold, we regress the log of the price p on a constant α, a set of time dummies, and parcel-specific characteristics. The time dummy D_i^{τ} is set to one if the transaction occurred at time τ and zero otherwise. In a daily price index, $\tau = T$ represents the last day, and $\tau = 0$ the first day in the sample, with the first dummy serving as the omitted category. This allows the coefficients β^{τ} to be interpreted relative to the first day. The term z_n^k denotes the k^{th} characteristic of parcel n. ϵ_t is the error term.

Fortunately, it is unnecessary to include as many characteristics (z_n) as would be required for real-world land or real estate data. As previously discussed, each parcel is uniformly sized. However, we know from Goldberg et al. (2024) that the location of a parcel is an important determinant of its value. We include three different location-related characteristics (z_n) for each parcel: the distance to the nine plazas and adjacency to a district as well as to a street. Additionally, we employ a dummy variable to indicate whether the parcel's coordinates are numerically memorable, defined as having identical

[6]For a more detailed description of the method, see European Commission. Eurostat. (2013).

absolute x and y coordinates.

In order to obtain as much information as possible about the effects of location, while accounting for the fact that many of the variables are correlated with each other, we estimate equation (1) using four different specifications.

For all specifications, we use dummy variables that are equal to one if a parcel is adjacent to a given district and zero otherwise. We also always use a dummy that tells us whether the parcel is adjacent to a street and the aforementioned dummy for easy-to-remember coordinates. The specifications differ in their consideration of distances to plazas. The distance to a plaza is calculated as the Euclidean distance from the center of the parcel to the center of the plaza.

For specification (I), the log distance to the nearest plaza is used, regardless of the specific plaza. Table 1 indicates that an increase in distance by 1% is associated with a reduction in price by 0.24%: The further away the parcel is from a plaza, the lower the price. However, in this specification, we do not differentiate between the plazas. Plaza 1, in particular, has a distinctive position: it is not only the center of the map, but also serves as the point of origin for all avatars upon logging into Decentraland. Consequently, we utilize the log distance to Plaza 1 and the smallest log distance to the other plazas for specification (II). The coefficient associated with Plaza 1 is more negative than those associated with the other plazas.

Table 1: The effect of LAND characteristics

	(I)	(II)	(III)	(IV)
Distance nearest plaza	−0.240 [0.007***]			−0.992 [0.039***]
Distance plaza 1		−0.184 [0.009***]		
Distance nearest plaza (2-9)		−0.113 [0.010***]		
Nearest plaza (Plaza 1 omitted)				
Plaza 2			−0.179 [0.017***]	−2.510 [0.166***]
Plaza 3			−0.124 [0.020***]	−2.971 [0.207***]
Plaza 4			−0.270 [0.015***]	−2.737 [0.164***]
Plaza 5			−0.326 [0.014***]	−2.942 [0.156***]
Plaza 6			−0.336 [0.014***]	−2.942 [0.156***]
Plaza 7			−0.321 [0.014***]	−3.229 [0.149***]
Plaza 8			−0.187 [0.015***]	−3.111 [0.157***]
Plaza 9			−0.168 [0.017***]	−3.136 [0.170***]
Distance nearest plaza × Nearest plaza (× Plaza 1 omitted)				
Plaza 2				0.705 [0.047***]
Plaza 3				0.827 [0.059***]
Plaza 4				0.738 [0.046***]
Plaza 5				0.840 [0.043***]
Plaza 6				0.772 [0.044***]
Plaza 7				0.859 [0.042***]
Plaza 8				0.854 [0.045***]
Plaza 9				0.868 [0.048***]
AETHERIAN Project	0.490 [0.066***]	0.527 [0.065***]	0.316 [0.068***]	0.396 [0.070***]
Vegas City	0.386 [0.044***]	0.404 [0.043***]	0.168 [0.045***]	0.253 [0.048***]
Dragon City	0.056 [0.019***]	0.076 [0.019***]	0.028 [0.021]	0.078 [0.021***]
Dragon Kingdom	0.158 [0.051***]	0.195 [0.051***]	0.079 [0.124***]	0.183 [0.051***]
Red Light District	0.131 [0.050***]	0.158 [0.049***]	0.133 [0.051***]	0.107 [0.050***]
University and Conference Center	0.226 [0.032***]	0.250 [0.032***]	0.095 [0.034***]	0.143 [0.034***]
Fashion Street	0.300 [0.031***]	0.344 [0.031***]	0.237 [0.033***]	0.259 [0.032***]
Road	0.408 [0.008***]	0.400 [0.008***]	0.435 [0.008***]	0.428 [0.008***]
Easy to remember	0.134 [0.078*]	0.065 [0.077]	0.105 [0.078]	0.149 [0.076**]
# obs.	24,232	24,232	24,232	24,232

Notes: The table shows the coefficients of the parcel characteristics (z_n) resulting from the estimation of equation 1. The estimates also include a constant and a time dummy for every day in the sample. ***, ** and * denote significance at the 1%, 5% and 10% level.

In specification (III), dummy variables are used to indicate which of the plazas are the closest to each parcel. The coefficients are estimated relative to Plaza 1 and are all negative. This implies that if a parcel has Plaza 1 as its closest plaza, the price there is significantly higher than if the parcel has one of the other plazas as its closest plaza. If plaza 6 is the nearest plaza, the effect is most pronounced in comparison to plaza 1.

The final specification (IV) incorporates interactions between the plaza dummies and the distance to the nearest plaza.

Across all specifications, it can be seen that direct adjacency to a district has a significantly positive effect on the price, as does adjacency to a road. Furthermore, coordinates that are easy to remember only have a significantly positive effect on the price for specifications (I) and (IV).

To sum up, our regression results identify several key location factors that significantly influence parcel values in Decentraland. These findings support the observations discussed in Chapter 2.3 central parcels near Genesis Plaza, particularly around coordinates (0, 0), command higher prices, while peripheral areas tend to have lower values. Similarly, proximity to prominent landmarks such as Fashion Street, District X, and Decentraland University, as well as community-driven projects like the AETHERIAN Project, enhances parcel value. Finally, parcels adjacent to major roads and plazas show higher values.

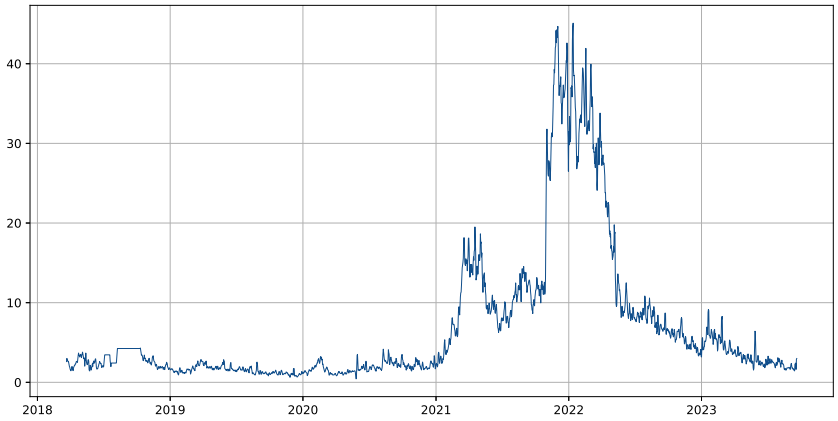
Controlling for the mentioned characteristics leads to the quality adjusted price index which can be calculated by:

$$P^{0\tau} = \exp(\hat{\beta}^t), \tag{2}$$

where P^{0t} is the price on day t relative to the base period ($t = 0$). $\hat{\beta}^t$ is the estimated β coefficient for day t from equation 1. Given that the resulting index exhibits relatively minor differences between the four specifications, we use the estimated beta coefficients from specification (I) for our baseline index.[7]

[7]Figure 18 in the appendix shows the indices resulting from all four specifications.

Figure 10: The Decentraland Price Index



Notes: This figure presents the Decentraland Price Index, derived from successful sales on the Decentraland platform, using the methods discussed in the text.

Figure 10 shows the resulting Decentraland Price Index, which begins on 20.03.2018. All values are interpreted relative to 19.08.2018, the official launch date of the Decentraland marketplace. By this point, the initial coin offering on 17.08.2017 and the first land auction on 15.12.2017 had already occurred.[8]

During the initial phase following the marketplace's opening, when only off-chain transactions were possible, the price index ranged between 0.23 and 4.8. Due to the low number of successful daily transactions, the index fluctuated significantly, with some days recording no transactions at all. For our subsequent empirical analysis, we use the index starting from 20.02.2020, the public launch date, when transactions became on-chain and accessible to all users. A notable spike in the index occurs on this day and the following day, reaching a value of 4.3, indicating that prices were 4.3 times higher than on the first day of our sample. Prices continued to rise steadily, reaching a new high of just under 23 on 03.05.2021 as Decentraland gained popularity, with companies and institutions establishing their first virtual branches. For

[8]For further details on land auctions and pricing, see Goldberg et al. (2024).

example, Sotheby's opened a virtual gallery on 04.06.2021. The hype period began in October 2021, with prices rising sharply thereafter. The rebranding of Facebook to Meta, announced on October 28, 2021, likely contributed to this surge, sparking increased interest in metaverse platforms such as Decentraland.

Our index peaked on November 1, 2022, when prices were almost 57 times higher than at the start of the sample period. However, within six months, prices fell drastically to around 5, and in the final third of our sample, values fluctuated significantly around this level.

In the next chapter, we will examine how the Decentraland Price Index (DPI) responds to real-world monetary policy.

4 The effect of monetary policy on Metaverse prices

Monetary policy impacts real-world housing or real estate prices through several direct and indirect channels. For instance, an increase in interest rates could raise the cost of credit or mortgages, which, ceteris paribus, would lower the demand for housing and subsequently lead to a decrease in prices. Moreover, if households anticipate this response and observe the rise in interest rates, their expectations may directly impact house prices via the expectations channel.

But why should we expect virtual real estate prices to react to real-world monetary policy? As mentioned above, virtual land prices exhibit characteristics that make them comparable to real land prices: parcels can be bought, sold, and rented to other users. If we assume that the price of a parcel can be approximated by the present value of future rental payments, we have:

$$P_t = E_t \left(\sum_{i=0}^{\infty} \frac{Q_{t+i}}{\prod_{j=0}^{i} R_{t+j}} \right) \tag{3}$$

Q is the rental payment and R the discount rate.

The key question is determining the relevant discount rate for users of the metaverse. If users invest and borrow exclusively within Decentraland and assume that the metaverse economy is entirely closed, then real-world monetary policy should have no effect on the discount rate and, consequently, on prices in Decentraland. However, we believe that this relationship is also influenced by the level of activity and popularity of the metaverse: the more users participate in the marketplace, the higher the likelihood that they are not exclusively active within the metaverse. Consequently, the transmission of real-world monetary policy becomes more relevant.

In such a market state, a positive monetary policy would likely increase the discount rate R and lead to a decrease in prices - mirroring the expected reaction in real-world markets. We will test these conjectures later in the paper.

Before proceeding, however, it is essential to define what constitutes real-world monetary policy in our context. Decentraland operates globally, and we lack information about the nationalities of individual users or which specific monetary policies are most relevant to them. Nonetheless, the Federal Reserve's (Fed) monetary policy is often considered particularly influential and is frequently used in such analyses.

Therefore, in the next section, we discuss the calculation of Fed monetary policy shocks and subsequently estimate their effects on metaverse prices.

4.1 Monetary policy surprises

To make causal claims about the effects of monetary policy, it is essential to identify exogenous or unexpected changes in the policy rate, often referred to as shocks or surprises. A common approach to constructing these shocks involves examining changes in relevant indicators on Federal Reserve meeting days. Some of these high-frequency shocks focus on changes in asset prices within narrow time windows, typically around 30 minutes, surrounding the meetings (as in Gertler and Karadi (2015), Nakamura and Steinsson (2018) or Bauer and Swanson (2023)). This small time interval is assumed to capture only the information released during the meeting, thereby isolating its

effect on asset prices. Moreover, asset prices should react only if something unexpected occurs during the meeting.

Unfortunately, no current versions of these shocks are available as of this writing. Therefore, we update the shock series by Bu et al. (2021), which is originally available until 2020. This shock series offers several advantages over the high-frequency shocks mentioned above. Specifically, it examines changes in zero-coupon rates of various maturities on meeting days, eliminating the need for sometimes noisy and difficult-to-access tick-data. The estimation process is straightforward, and the required data are readily accessible. Further, according to Brennan et al. (2024), unlike some high-frequency shocks, these shocks often produce results that are consistent with New Keynesian models.

Bu et al. (2021)'s method involves a two step Fama-MacBeth procedure. First, they assess the response of zero-coupon yields with maturities ranging from 1 to 30 years to a policy indicator. They estimate:

$$\Delta R_{m,t} = \alpha_m + \beta_m \Delta i_t + \epsilon_{i,t}, \qquad \text{for} \quad m = 1 \ ... \ 30, \tag{4}$$

where $\Delta R_{m,t}$ is the change in the zero-coupon yield at maturity m on day t, and Δi_t is the change in the policy indicator. Following Bu et al. (2021), we use the two-year Treasury yield. The day t can be either a meeting day or a day one week before a meeting. This follows from the heteroskedasticity-based identification of Rigobon and Sack (2004) used to estimate the equation above. The key assumption is that the monetary policy shock is heteroskedastic, i.e. the variance of the shock is higher on meeting days than on non-meeting days (e.g. seven days before the meeting), while other shocks are homoskedastic. Equation 4 can then be estimated using Δi_t and $-\Delta i_t$ as instruments for meeting and non-meeting days, respectively. To identify meeting days, we use the same dates as Bauer and Swanson (2023) and update them to the end of 2023. Our dataset spans from 1994 to the end of 2023.

The first step yields the estimated $\hat{\beta}$ coefficients for each maturity. In the second step, these coefficients are used to run a cross-sectional regression for

each meeting day t:

$$\Delta R_{m,t} = \delta_i + e_t \hat{\beta}_m + v_{m,t}, \qquad \text{for} \quad t = 1 \ldots T, \tag{5}$$

where the resulting coefficients e_t are the monetary policy shocks.

In the case of a pure monetary policy shock, interest rates and stock prices are expected to move in opposite directions. However, it has been observed that stock prices sometimes move with interest rates. One explanation for this could be the presence of a central bank information shock, which occurs when the central bank releases previously unknown information about the economic outlook during its meetings. According to Bu et al. (2021), their shock series captures a pure monetary policy shock and explicitly excludes central bank information shocks.

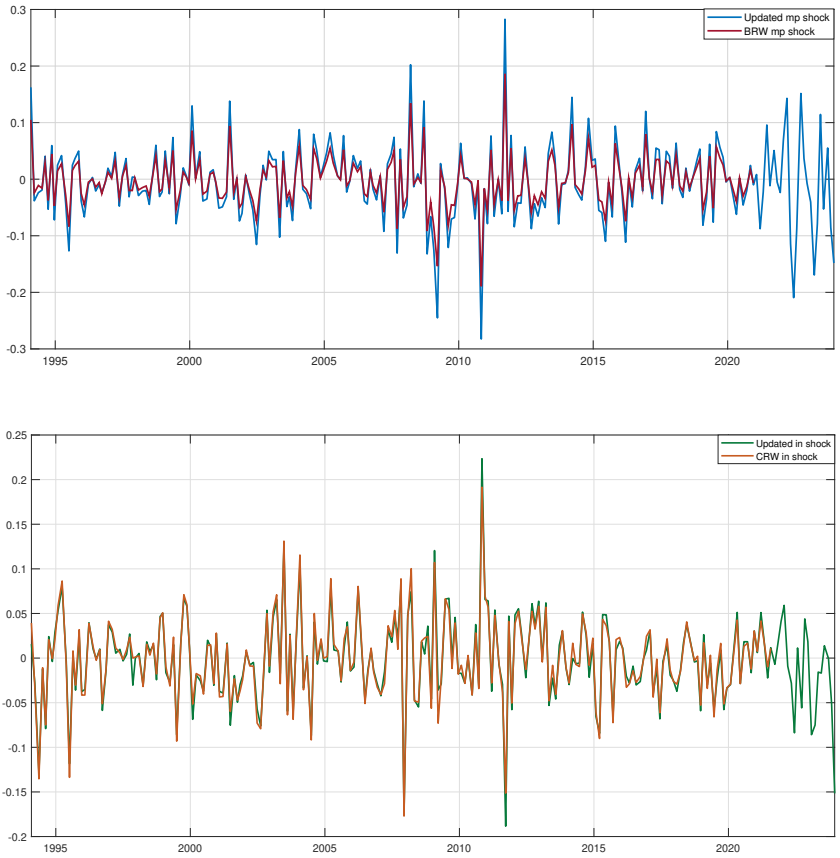
Building on this, Ciminelli et al. (2022) extend the procedure of Bu et al. (2021) by estimating information shocks through a simple regression of the change in the policy indicator on the monetary policy shock:

$$\Delta i_t = \theta_t + \gamma \hat{e}_t + \xi_t, \tag{6}$$

where the residuals ξ_t are the information shock.

Figure 11 shows the estimated shock series alongside the original shocks. As observed, our updated shocks are highly correlated with the originals, although they should not be exactly identical due to a larger sample size and slightly different meeting days. In contrast to Bu et al. (2021), who only include regular meeting days, we also consider irregular meeting days.

Figure 11: Pure monetary policy (mp) and information news (in) shocks



Notes: The figure shows the updated monetary policy and information shocks, derived using the method of Bu et al. (2021) and Ciminelli et al. (2022), alongside the original shocks.

4.2 Linear model

After calculating the shock series, we use local projections (Jordà, 2005) to estimate daily effect of FED'S monetary policy on Decentralands' prices:

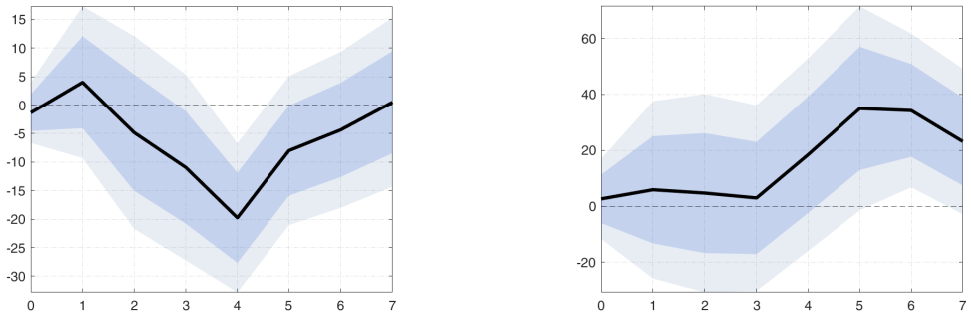
$$DPI_{t+h} = \alpha_h + \beta_h \epsilon_t + \gamma_h X_t' + \eta_{t+h} \tag{7}$$

DPI is the log of the 3-day moving average of our Decentraland price index multiplied by 100. ϵ_t is either our pure monetary policy shock or the infor-

mation shock. The daily series takes the value of the corresponding shock on meeting days and is zero otherwise. We further include control variables (X_t). We use the log of the VIX of the S&P500, the Daily News Sentiment Index, as described in Shapiro et al. (2020) and interest rates measured through the 10-year US Treasury Bond (GS10) as control variables for real-world economic conditions. To control for developments in the crypto market, we use the first principal component of selected cryptocurrencies. We further estimate the model with seven lags of the dependent variable DPI, the exogenous control variables and the shock, repectively. Our sample spans from 20th February 2020, the day of the public release, until 20th September 2023. The variables of interest are the β_h-coefficiants measuring the response of the decentraland prices h days after the shock occurs. If monetary policy has an effect on prices in the metaverse, we would expect prices to fall after a positive pure monetary policy shock and to rise after a positive information shock.

Figure 12 plots the estimated β_h coefficients. In case of a positive monetary policy shock of 25 basis points prices in decentraland fall by about 20%. This pronounced effect, however, is only significant at the 90% significance level on the fourth day after the shock.

Figure 12: The response to a monetary policy and central bank information shock



(a) Pure monetary policy shock

(b) Information news shock

Notes: This figure shows the daily responses of Decentraland prices to a 25-basis-point monetary policy (a) and information (b) shock. The shaded areas represent the 68% and 90% probability bands.

If we look at the effects of an information shock, we can also observe the expected sign here: prices rise by up to 38%. Again, this effect is only significant on one day, six days after the shock occurs.

4.3 Different states of user activity

The number of users in Decentraland fluctuates considerably over our sample period. Following the official launch of Decentraland in February 2020, user numbers remained relatively low before experiencing a significant increase during the hype period, only to decline again thereafter.

We argue that the effect of monetary policy varies depending on the state of user activity. When activity is high, and a large number of users are actively buying and selling land parcels, the effect of monetary policy should closely mirror that observed in real-world markets. Specifically, we expect prices to fall following a monetary policy shock and to rise in response to an information shock when user activity is high. However, when user activity is low, the effects are less predictable. To test this, we estimate state-dependent

local projections:

$$\text{DPI}_{t+h} = \alpha_h + F(a_{t-1})[\beta_h^{high}\epsilon_t + \gamma_h^{high}\mathbf{X}_t'] + (1 - F(a_{t-1}))[\beta_h^{low}\epsilon_t + \gamma_h^{low}\mathbf{X}_t'] + \eta_{t+h} \tag{8}$$

In this smooth transition model, the effect of the shock on the dependent variable is a weighted average of the effects in high and low activity states. The weight of each regime for each observation is determined by $0 \leq F(a_{t-1}) \leq 1$. We follow Born et al. (2020) and use the empirical cumulative distribution function of the state variable. We measure activity in Decentraland by the number of successful sales recorded in our transaction database and use the lagged series of this measure as our state variable a_{t-1}.

The transition function evolves as:

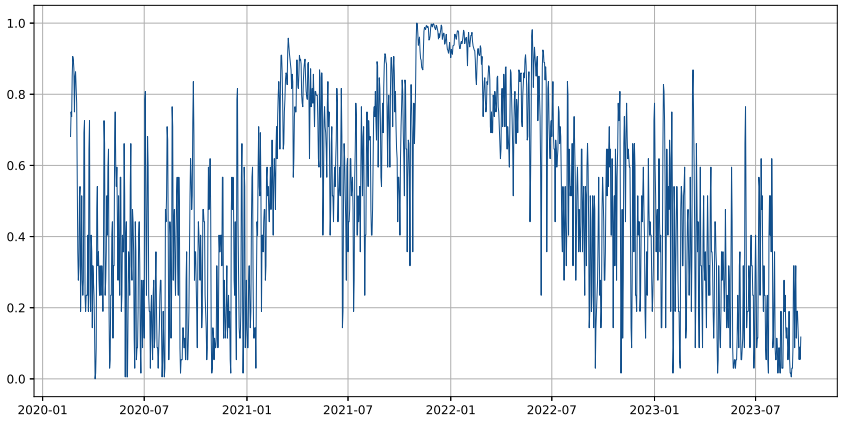
$$F(a_{t-1}) = \frac{1}{N}\sum_{j=1}^{N} \mathbb{1}_{a_j \leq a_{t-1}}, \tag{9}$$

where N is the number of observations in our sample, and $\mathbb{1}$ is an indicator function that equals one if $a_j \leq a_{t-1}$ and zero otherwise. Further, $F(a_{t-1}) = 0$ if the state variable is at its minimum and $F(a_{t-1}) = 1$ when it is at its maximum. The advantage of this method is that it does not require further assumptions about the parameters of the transition function, unlike the approach used by Auerbach and Gorodnichenko (2012).

Figure 13 plots the values of the transition function which can be interpreted as the probability of being in the high activity state. Immediately after the official launch of Decentraland, high probabilities of being in the high activity state are observed. Following this, the probabilities decline but exhibit substantial fluctuations. Notably, the probabilities increase again after Meta's rebranding in February 2021. Thereafter, the state variable reaches its peak during the hype period between November 2021 and January 2022, with the probabilities of being in a high state approaching one. Subsequently, the weights decrease again, showing considerable variation between very high and very low probabilities.

We estimate Equation 8 using the described transition function and the same variables as in the linear model. Figure 14 presents the corresponding

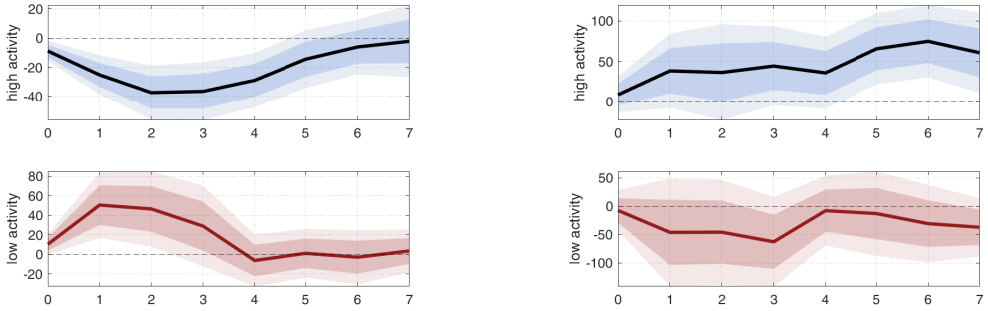
Figure 13: Transition function $F(a_{t-1})$



Notes: This figure shows the values of the transition function $F(a_{t-1})$ based on the method of Born et al. (2020). State variable is the number of successful sales in Decentraland.

impulse responses. We see much clearer effects of the shocks compared to the linear model. In the case of a monetary policy shock and high activity, prices react even on impact and fall by up to 40% on the third day after the shock, while they rise in the case of low activity. Overall, the effects are not very persistent. In the high state, the effect disappears on the sixth day, in the low state on the fourth day.

Figure 14: The response to a mp and in shock under different states of user activity



(a) Pure monetary policy shock

(b) Information news shock

Notes: This figure shows the daily responses of Decentraland prices to a 25-basis-point monetary policy (a) and information (b) shock under two different states of user activity. The state variable is defined as the daily number of successful sales. The shaded areas represent the 68% and 90% probability bands.

Even with an information shock, prices react more strongly than with the linear model when activity in decentraland is high. They rise to a maximum of 70% on the sixth day, while no significant effects can be detected with low activity.

In summary, Decentraland prices respond to pure monetary and information shocks in high user activity states with the expected signs, similar to their real-world counterparts. However, there are notable differences: First, while real-world prices tend to react with a delay, the DPI in Decentraland responds immediately or within just a few days. Second, these effects are very short-lived; no significant impact can be detected after a week at the latest. Third, the magnitude of the effects is substantial.

We use the results from our state-dependent model as baseline for the following robustness analysis.

4.4 Robustness

We use the number of successful sales as the state variable for our previously discussed baseline results. This variable derives from our self-collected trans-

action dataset. We now examine whether our results remain robust if we change the state variable to one not self-collected or constructed by us. We therefore use the daily number of active wallet addresses in Decentraland, as reported by Messari.[9] Figure 15 illustrates the corresponding impulse responses. As is apparent, a positive monetary policy shock leads to an immediate and significant drop in prices when user activity is high. The effect persists for approximately 4 to 5 days and yields values very similar to our baseline results. If user activity is low, we again observe a positive effect on prices. Also the effects of the information news shock mirrors our baseline results closely: Prises experience a rise of about 50% which is only significant to the 90% level at the sixth day after the shock when user activits is high. We don't see an effect in the low user activity state.

As Brennan et al. (2024) show, monetary policy shocks can sometimes differ greatly depending on the methods and data chosen. Since there are only a comparatively small number of meeting days in our sample, the choice of monetary policy shock could have a significant influence on our results. We therefore estimate equation 8 using the updated version of Jarociński and Karadi (2020)'s monetary policy and information shocks. They use high-frequency data around FOMC meetings and estimate the shocks using a baysian VAR and sign restrictions. Figure 16 shows that our main results hold even with these shocks. With high user activity, we see a negative effect of a monetary policy shock with very similar values to our baseline estimate. The effect of information shocks is positive in the high state, but the estimated coefficients are not significant. We see no effects of monetary and information shocks on prices when activity is low.

Finally, we test whether our results depend on the chosen method of state-dependent local projections. We now use the approach of Auerbach and Gorodnichenko (2012) and Tenreyro and Thwaites (2016). This differs from the method by Born et al. (2020) in the calculation of the transition

[9] www.messari.io

function $F(act_{t-1})$, which is now expressed by a logistic function:

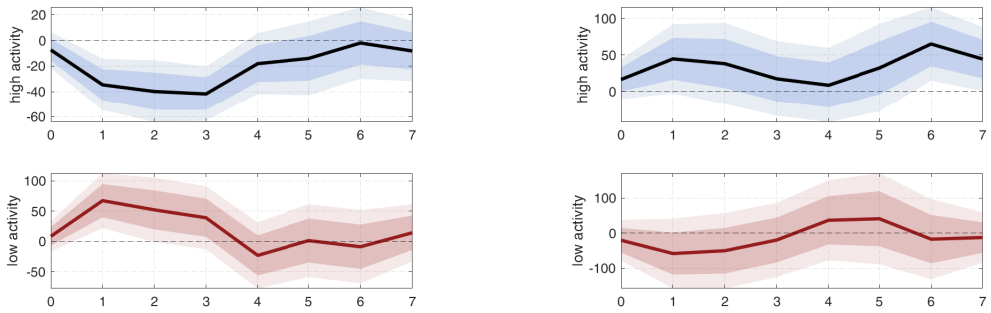
$$F(z_t) = \frac{exp\left(\theta \frac{z_t - c}{\sigma_z}\right)}{1 + exp\left(\theta \frac{z_t - c}{\sigma_z}\right)} \tag{10}$$

θ measures the smoothness of the transition between the two states, with higher values indicating a smoother transition. As common in the literatur, we set θ=3. We set c, such that for 30% of the time Decentraland is in the high activity state.

Figure 17 shows the resulting impulse responses, which closely mirror our baseline results. Even the values for both states and shocks are nearly identical to those observed previously.

In summary, our findings remain robust with respect to alternative state variables, shocks, and transition functions.

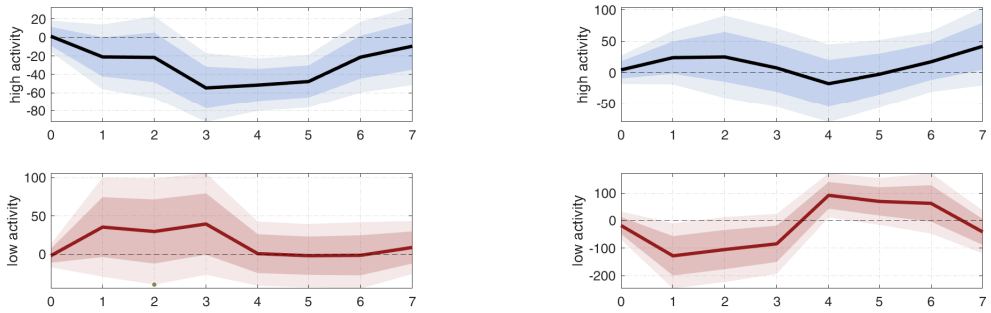
Figure 15: The response to a monetary policy and central bank information shock: Alternative state variable



(a) Pure monetary policy shock (b) Information news shock

Notes: This figure shows the daily responses of Decentraland prices to a 25-basis-point information shock under two different states of user activity. The state variable is defined the daily number of active addresses. The shaded areas represent the 68% and 90% probability bands.

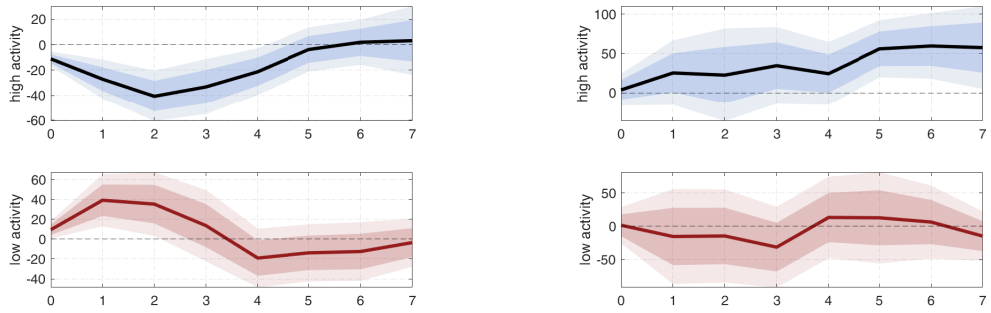
Figure 16: The response to a monetary policy and central bank information shock: Alternative shock series (Jarociński and Karadi, 2020)



(a) Pure monetary policy shock (b) Information news shock

Notes: This figure shows the daily responses of Decentraland prices to a 25-basis-point monetary policy (a) and information (b) shock under two different states of user activity. The state variable is defined as the daily number of successful sales. The shaded areas represent the 68% and 90% probability bands.

Figure 17: The response to a monetary policy and central bank information shock: Alternative transition function (Auerbach and Gorodnichenko, 2012)



(a) Pure monetary policy shock (b) Information news shock

Notes: This figure shows the daily responses of Decentraland prices to a 25-basis-point monetary policy (a) and information (b) shock under two different states of user activity. The state variable is defined as the daily number of successful sales. The shaded areas represent the 68% and 90% probability bands.

5 Conclusions

This paper examines the effects of real-world monetary policy on virtual land prices. We collect relevant on-chain transaction data from various marketplaces and construct a price index to capture the price dynamics of virtual real estate on the platform. Our findings demonstrate that virtual prices do respond to Federal Reserve monetary policy, despite the often-emphasized closed and unique nature of virtual worlds. Using state-dependent local projections, we observe that when activity and popularity in the virtual world are high, prices respond to monetary policy and information shocks in the expected direction, mirroring real-world reactions.

However, important differences are evident: Prices in the metaverse react much faster, either immediately in the case of a pure monetary policy shock or within a few days following an information shock. Additionally, the effects are short-lived, disappearing within a week. Finally, the magnitude of the effects is substantial, with prices responding even more strongly to information shocks.

Understanding the economic dynamics of virtual real estate offers valuable insights for investors and developers aiming to capitalize on metaverse opportunities. Our findings equip stakeholders with the ability to make informed decisions in anticipation of monetary policy trends, while also highlighting the importance of managing risks associated with policy-induced price volatility to ensure the resilience of virtual asset investments against macroeconomic fluctuations. By providing empirical evidence on how monetary policy impacts virtual real estate prices, we contribute to the broader discourse on the increasing interconnection between digital and physical economic realms. These insights will be crucial for policymakers, investors, and developers navigating the evolving metaverse landscape.

Furthermore, by demonstrating that economic mechanisms and reactions also apply in the metaverse, our findings suggest that the metaverse can serve as a valuable setting for further economic research. For instance, field experiments that would be challenging to conduct in the real world become feasible in the metaverse due to a crucial property: virtually all behavior is

observable.

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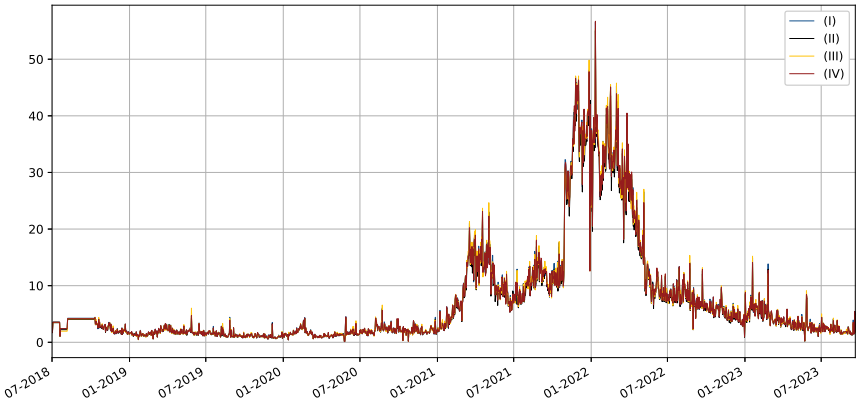
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Appendices

Figure 18: Specifications (I) to (IV)



Notes: The figure shows the different specifications of the Decentraland Price Index derived from equation 1, varying by the choice of parcel-specific control variables.