The Origins of Inequality: A Natural Experiment in *Minecraft*

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Abstract

I study the emergence of inequality in a massively multiplayer natural experiment in Minecraft. I use machine learning methods and real-time activity and location data to estimate how random assignment of starting locations affects economic outcomes at the individual and group level. I find that the composition of food sources produced in a starting location has a significant causal effect on the level of inequality within groups of closeby players; the emergence of inequality depends on the interaction between four properties of food production: capital intensity, appropriability, renewability, and land dependence. Exposure to capital-intensive renewable food sources increases within-group inequality, primarily by raising outcomes for top earners at the expense of those at the bottom. These factors also have a significant effect on economic growth and wealth accumulation. I provide causal evidence in favor

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of historical theories of inequality, in particular, ones that suggest that capital-intensive highly appropriable food leads to long-term economic inequality.

1 Introduction

Much as nations differ in their wealth, they also differ in their inequality. While some of this variation reflects differences in policies and institutions (Piketty 2000, 2014), a central question is how inequality and institutions emerge. A growing literature in economics links the rise of persistent inequality to the transition from egalitarian hunter-gatherers to hierarchical farming states at the end of the Neolithic Age. There are competing explanations for this emergence of inequality, such as technological shifts in production (Bowles and Fochesato, 2024), the formation of the state (Acemoglu and Robinson, 2012), and changes in cultural attitudes toward inequality (Graeber and Wengrow, 2021). Yet because of limited archaeological evidence, these hypotheses remain difficult to test. In particular, we lack a setting in which technology, institutions, and social norms can be credibly and exogenously perturbed.

This paper develops a new empirical approach to identifying the origins of inequality using real-time location and activity from a persistent multiplayer economy. The analysis exploits a natural experiment in which initial conditions – specifically, randomly assigned starting locations – generate exogenous variation in resource availability, production technologies, and social organization. Because participants start with identical endowments in the experiment, differences in subsequent economic development can therefore be causally attributed to the features of a participant's starting location. This approach allows me to estimate how initial conditions shape economic outcomes such as production, social organization, and the distribution of wealth.

This paper builds on a literature on virtual worlds in economics that has primarily focused on (i) leveraging the immersive and complex properties of video games for large-scale observational studies that would not be possible in the real world, or (ii) running lab experiments that benefit from the flexibility of video game interfaces in representing different relevant domains for research.[1] My contribution bridges these two strands of literature together by studying a natural but replicable field experiment in a massively multiplayer virtual world that allows me to answer questions in political economy and economic development. Although there are other papers in experimental economics that address similar questions (Kaplan et al., 2014 and 2018), this paper differs by studying the emergence of inequality in a larger and more complex setting.

The empirical setting is *Minecraft*, a three-dimensional multiplayer online survival video game that features a persistent, player-driven economy. Participants begin with no resources to their disposal and must acquire them from their environment in order to survive. A key feature of the game is the hunger system, which requires players to produce or acquire food from a diverse set of food types that differ in their production technology and their spatial distribution. These differences generate comparative advantages that shape specialization, cooperation, and exchange. Because participants can self-organize into communities that manage resources and institutions, these comparative advantages translate into diverse forms of social organization. This diversity provides the setting with sufficient complexity to observe a broad distribution of institutional outcomes and to identify which features of the initial environment give rise to those institutional differences.

The natural experiment is as follows. When a participant enters the game, they may either join an existing group or start in a random location; those who start randomly are exogenously assigned to starting locations that may already contain other players, resources, and local institutions that have endogenously developed over time. This assignment generates exogenous exposure to heterogeneous social and institutional environments shaped by the prior behaviors, norms, and production choices of nearby participants. The analysis focuses on the features of randomly assigned locations, so that differences in subsequent outcomes can be attributed to exogenous exposure to local environments. All participants begin with no material assets and must acquire resources to survive threats including hunger, environmental hazards, computer-controlled enemies, and potentially nearby players. To analyze the effects

[1] For examples of the first, see Castronova (2001), Castronova et al. (2009), Garnett et al. (2014). For examples of the second, see Chesney, Chuah, and Hoffman (2009), Greiner, Caravella, and Roth (2014), Duffy (2011), and Innocenti (2017).

of this random exposure, I use a novel dataset from the *Stoneworks Minecraft* community that records players' actions and 3-D locations in real time. These records capture a variety of economic behaviors, allowing me to track the evolution of individual and group outcomes over time. Combined with a detailed map of the world, I infer local resource distributions and identify cohabiting groups that interact within the same areas as the game progresses.

The dynamics of Stoneworks Minecraft's economy resembles that of the real world's economy in many dimensions. Over the 3-month study period, the GDP and GDP-per-capita of this economy grows at an annual rate of 2.1% and 1.4% respectively. However, this growth is not distributed equally across the economy as there is substantial inequality both within and between groups of players. There is persistence in the methods of acquiring income and wealth over time, with different groups of players selecting different strategies for wealth accumulation. This persistence over time also carries over to the way players acquire and produce food. An integral component of this economy, especially relevant for studying early economic development, is conflict. The game allows players to wage war against each other, temporarily suspending property rights and allowing territorial conquest to take place. The ability to make and enforce threats over resources is essential for testing theories that link resource appropriability to the emergence of inequality (e.g., Mayshar, Moav and Neeman 2017; Mayshar Moav, and Pascali 2022; Huning and Wahl 2023).

I estimate how income and wealth inequality are causally affected by resource availability, production technology, and social organization. The key source of identification is the random assignment of starting locations, which ensures that players are ex ante identical in expected outcomes. Because each location bundles multiple features at the same time, I estimate the marginal treatment effect of each feature using a high-dimensional regression framework that isolates the partial effect of each feature while holding other features fixed. To limit false positives from multiple hypothesis testing, I adjust p-values using the procedure from Romano and Wolf (2016).

The results show that income and wealth inequality within groups are primarily shaped by the composition of food sources produced nearby. Locations where nearby players rely on capital-intensive, easily appropriable, renewable, and non-land-dependent food sources exhibit significantly higher income inequality. A one-percentage-point increase in the local share of such foods raises the daily income Gini by roughly 0.6 percentage points and increases an individual's probability of belonging to the top income decile by about 0.9 percentage points. In contrast, wealth inequality is mitigated where food production is capital-intensive, difficult to appropriate, renewable, and land-dependent, reducing the wealth Gini by about 1.9 percentage points for a one-percentage-point increase in exposure.

Decomposing these effects into individual food sources suggests that inequality rises where production technologies combine high fixed investment costs with high appropriability and falls where production requires multiple inputs or dispersed resources, which limits elite appropriation and disperses income sources. Additional estimates show that wealth inequality increases modestly with local food-related purchases and average wealth but declines with higher local tax payments, indicating that redistribution mechanisms can emerge even in this decentralized setting.

Finally, the same environmental characteristics that amplify inequality also affect economic growth. Capital-intensive, hard-to-appropriate, non-land-dependent renewable foods substantially increase group income and wealth (by 6 and 11 percent, respectively), whereas capital-intensive, easy-to-appropriate, land-dependent renewable foods reduce both. These findings imply that initial conditions shape both the level of economic development and its distribution, offering a micro-causal perspective on the mechanisms through which inequality and growth co-evolve.

Taken together, these findings provide causal evidence on how environmental and technological conditions shape inequality and growth through endogenous processes of production and organization. By isolating the role of exogenous variation in local environments, the analysis complements historical and theoretical work on the origins of inequality (e.g., Bowles and Fochesato 2024; Acemoglu and Robinson 2012) with micro-level evidence from an experimental setting where institutions emerge endogenously. The results highlight that inequality can arise not only from policy or institutional capture but also from the economic technologies and resource ecologies that enable differential appropriation of surplus.

The remainder of the paper is organized as follows. Section 2 describes the game environment. Section 3 outlines the empirical strategy. Section 4 presents the main results of the paper. Section 5 discusses the implications of these findings for theories of inequality and development, and Section 6 concludes.

2 Minecraft and the Stoneworks Economy

In this section, I explain the features of Minecraft as well as the specific setting (Stoneworks Minecraft) of the natural experiment.[2]

2.1 Basic Systems

Minecraft is a 3-D video game in which players interact with a procedurally generated world composed of discrete units ("blocks") representing different materials such as dirt, sand, or water (see Figure 1). Players control individual avatars that can move through and alter the environment by collecting, combining, and placing blocks. The world of Minecraft is viewed primarily in first-person, meaning that players experience it as if through the eyes of their avatar.[3] Because visibility is limited to the avatar's immediate surroundings, players operate with partial information about the environment. This forces search and localized decision-making about where to move and what to produce.

The game's environment is generated algorithmically rather than designed manually, ensuring that each game instance features distinct topography and resource distributions. These environments are divided into "biomes", such as forests, deserts, and mountains, each associated with different resource endowments. Because biome generation is randomized, the spatial distribution of resources is effectively predetermined by the game's random seed and not by the players. This prevents players from predicting or choosing what resources they have available to them in unexplored areas of the environment, creating exogenous heterogeneity in local production possibilities and hence in comparative advantage.

[2]Readers already familiar with Minecraft but not Stoneworks specifically can skip to section 2.2. Readers which are familiar with both can skip directly to section 3.

[3]For the reader unfamiliar with first-person games, see Figure A1 in the Appendix for an example of a first-person (and third-person) perspective.

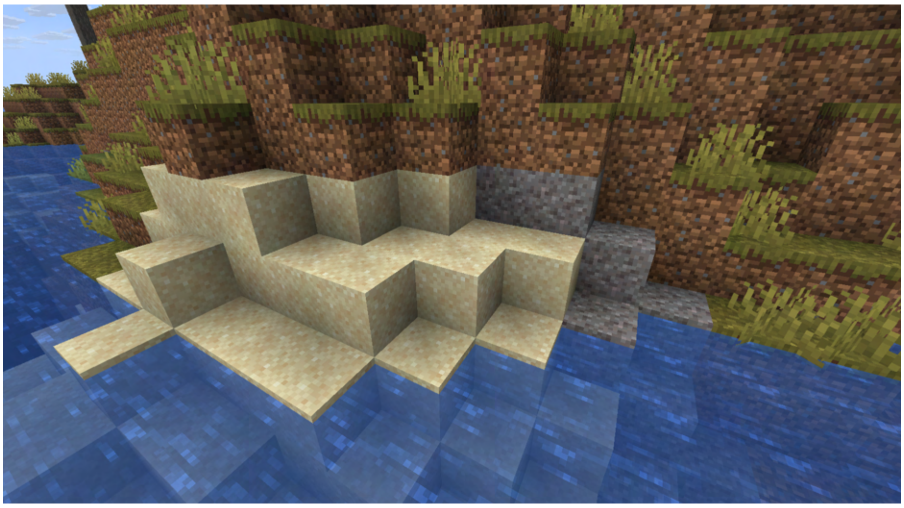

Figure 1: A procedurally generated coastline in Minecraft. Each "block" represents a distinct material: at the top of the picture, there are grass blocks; in the middle, sand, dirt, and gravel blocks; at the bottom, water blocks.

The game can be played in either *singleplayer* or *multiplayer* mode. In the latter, all players inhabit a common environment that continues to evolve even when individual users log off, allowing for decentralized interactions and long-run social dynamics. The defining characteristics of Minecraft align closely with the concept of a *virtual world* as described by Bartle (2004): it possesses internal physics, persistent states, real-time interaction, and shared space mediated through avatars. These properties jointly create a self-contained environment in which individual actions generate observable, path-dependent changes to the world. For quantitative research, this persistence and interactivity make the world not only economically interpretable but also data rich, as each action and movement can be recorded in real time.

In the standard *Survival* mode of Minecraft - which is the setting applicable to this paper - players begin with no material assets. They must gather resources, produce goods, and manage their avatar's health and hunger to avoid death. Minecraft's hunger system functions as a subsistence constraint that requires players to exert effort in acquiring food either through production or trade. Resource accumulation requires transforming raw materials into intermediate goods and tools through Minecraft's *crafting* system. The crafting system forms a complex and combinatorial task hierarchy (Guss et al., 2019). Because many tools are intermediate inputs into more complex ones, production exhibits complementarities, making specialization within groups natural.

These interlocking systems generate a natural structure of production, specialization, and exchange. Even in small-scale multiplayer sessions, players spontaneously form cooperative arrangements to pool resources and divide tasks (e.g., mining, farming, defense, or trade). The economy thus arises endogenously from the rules of the environment rather than from any explicit objective or instruction, mirroring how the economy emerges from fundamental constraints and incentives.

2.2 Stoneworks Minecraft

Minecraft's multiplayer mode allows players to host independent "servers" — shared instances of the game where customized rules and modifications can be applied to change how the game works. There are thousands of such servers operating in any given day, each with its own economic and institutional systems. To study how initial conditions shape economic development, I study a specific server of Minecraft known as *Stoneworks* for a period of three months (from October 18, 2024 to January 17, 2025) in which I observe the universe of user activity and locations. Created and maintained by the owner of the *Stoneworks* YouTube channel, Stoneworks modifies the base game to introduce institutions that mirror property rights, markets, taxation, and political organization within a shared virtual environment. The current iteration of Stoneworks has been operating continuously since April 2024, hosting tens of thousands of players who interact within a single persistent economy.

There are two key extensions from the basic systems of Minecraft that transform Stoneworks into a suitable system to study early economic development. Both systems are implemented through third-party "plugins" that allow servers to add programmable rules to the base game.

The *ChestShop* system introduces a fully automated currency-based economy. Players can deposit goods into storage chests and set prices for buying and selling those goods. Other players can then transact directly with a player's storage chest ("chestshop"), buying or selling goods from the shop owner without the owner needing to be present. The game's administrators maintain a limited number of "AdminShops" that buy and sell certain goods in unlimited quantities and at fixed prices, effectively establishing an official exchange rate between certain items and the in-game currency, the Stoneworks coin (S$). AdminShop activity effectively injects and absorbs currency into the economy; prices for non-AdminShop items are set by players in private chestshops. This system eliminates the double-coincidence problem of barter and allows prices, incomes, and expenditures to be observed and compared directly. At the same time, this provides a policy tool for Stoneworks' administrators to control the in-game economy by changing the exchange rates. The administrators' periodic adjustments to the AdminShop exchange rates affect the aggregate money supply and relative prices. I absorb these common shocks in my analysis by using period fixed effects in the empirical analysis in section 3.

The *Lands* system defines property rights and territorial organization. For a substantial upfront cost, players can claim parcels of land ("chunks") that become protected from modification by others, creating enforceable ownership and exclusion. Claimed lands can be grouped into *towns*, within which owners can levy taxes. Towns may further organize into *nations*, which can collect inter-town taxes and coordinate defense and external relations. Together, these institutions allow players to form endogenous governance structures (towns and nations) with enforceable property rights recognized by the game's rules.

Conflict and appropriation are integral components of this system. Nations may formally declare war on one another, which temporarily suspends protection rights and allows territorial conquest to occur. These conflicts are initiated and directed by players, but scheduled and announced by the game's administrators. During wartime, players who die can lose their possessions to the victors, which enables forceful redistribution and deterrence effects that are important in emulating dynamics present in early historical states. The ability to make and enforce threats over resources is essential for testing theories that link resource appropriability to the emergence of inequality (e.g., Mayshar, Moav and Neeman 2017; Mayshar Moav, and Pascali 2022; Huning and Wahl 2023).

While conflict is a recurrent feature, much of the activity in Stoneworks is also cooperative. Players frequently form alliances, trade networks, and collective institutions for managing public goods. New players can join existing towns voluntarily or start independently in a random location, the latter forming the basis of the natural experiment used in this paper. The diversity of institutions that emerges, from feudal kingdoms and nomadic tribes to free-market democracies and socialist communes, arises endogenously from player interaction rather than top-down design.

However, not all the social organization in Stoneworks occurs entirely within the game. Stoneworks players also organize themselves on a public *Discord* server with more than 65,000 users. While I do not observe individual demographics, YouTube viewer analytics for the Stoneworks YouTube channel suggest that participants are predominantly young men between 18 and 34. I discuss how the representativeness of the sample may affect the external validity of my results in section 5.4; if I assume that the study sample differs only in age and gender composition to that of a more representative sample, I argue that the expected differences in players' social preferences ought to be small. Nonetheless, these skewed demographics indeed limit my ability to infer how women and older players would organize themselves differently than men in Minecraft. Likewise, there could be unobservable differences which could easily alter the type of institutions players are likely to form in such a way that the results of this paper may not generalize to a more representative study (e.g. players interested in Stoneworks Minecraft might have unusual social preferences in a way which typical young men do not).

3 Estimating the Effect of Starting Locations

In this section, I showcase the data sources in this study and explain my empirical strategy to convincingly get exogenous variation and identification at the same time. The central identification assumption relies on the idea that there are no omitted relevant features that could affect relevant outcomes after accounting for the resources immediately visible in a starting location and a wide variety of possible features.

3.1 Data Sources and Measurement

There are two main sources of data: real-time records of user activity in Stoneworks and a detailed map of the world of Stoneworks that allows me to infer the distribution of resources on the surface.

3.1.1 Real-time records

The real-time data is recorded primarily through a SQL database managed by an anti-griefing plugin called *CoreProtect* and the shop records from the *ChestShop* plugin.

CoreProtect tracks three main categories of user activity: session data, item data, and command data. In all cases, the data is stored with precise 3-D coordinates for any user interaction as well as timestamps accurate to the nearest second. The data available to me only goes from October 9, 2024 to July 15, 2025 (about 10 months of data), which is about six months after the current instance of Stoneworks Minecraft began in April 14, 2024.

Session Data. This provides a record of when every player logs in and out of Stoneworks Minecraft, including their avatar's location at the moment of entering and leaving the game. This also lets me back out the amount of time a user is playing the game as well as identify a player's first time within the game, which is important for identifying a player's starting location.

Item Data. This provides a record of whenever a player picks up, drops, crafts, or uses an item for crafting as well as whenever players shoot arrows. The record includes the identity and quantity of the item involved in the activity. This data is crucial for identifying the extraction of raw resources and the production of items, as well as whether the acquisition of certain items comes about through simply receiving (voluntarily or involuntarily) an item from another player or through domestic production.

Raw resource extraction in Minecraft usually involves breaking blocks which creates "drops" of the resource that can then be "picked up" into a player's inventory.[4] This effectively means that all raw resource extraction shows up in the data as pickups. In some cases, however, pickups can be a misleading proxy for resource extraction if player drops are unaccounted for.

Just as breaking blocks can create drops of a resource, players can also drop items and resources either voluntarily or by being killed in a war. These are the drops

[4]This process is illustrated visually in Figure A3 in the Appendix, showing how a player can obtain dirt and then place it.

that appear in this data source whereas drops from breaking blocks are excluded. While players are able to make transfer payments in terms of money, drops are also a common method of making informal exchanges of resources by having each party of the exchange drop the items they wish to offer in the exchange and then having players pickup the items that they want. Since these pickups also show up in my data but they require drops in order to happen, I can infer the amount of resource extraction by the excess pickups of resources after accounting for the number of drops made of an item within an area and period of time.

As I mentioned before, items are produced in Minecraft primarily through its crafting system. Producing items through crafting requires the use of inputs (raw resources or other items) which are then transformed into the item of interest.[5] The item data records the entire production process, ensuring one can account for the use of inputs and avoid double counting when measuring item production: the raw resource extraction of chopping down a tree would show up as pickups of oak logs, the transformation from oak logs to oak planks would show up as "uses" of the oak logs to then "craft" the oak planks, the transformation from oak planks to a crafting table would show up as using planks for crafting the crafting table, and finally, the use of planks for creating a chest would also show up in the data. However, the placing of the crafting table and the storage chests would not be observed in my dataset.

Finally, Minecraft has a wide variety of weapons, one of which is a bow that can shoot arrows provided a player has at least one arrow. The item data records the use of arrows from shooting them from a bow, which serves as a partial measure of when players are engaged in ranged combat. This measure turns out to be irrelevant in the analysis but it is nonetheless included for completeness.

Altogether, the item data provides the universe of player interactions regarding resource extraction and item production.

Command Data. This provides a record of when players make use of plugin commands, including those implemented as part of the Lands and ChestShop plugins.

[5]Figure A4 in the Appendix shows the procedure through which a storage chest is created in Minecraft.

This record includes all attempted commands from players, including making transfer payments and land claims, transferring ownerships of land, managing town and nation taxes, accepting, rejecting, and making invitations from/to players to/from other towns, and making tax payments and withdrawals to and from town coffers.

An important aspect of this data source is that the command data has substantial measurement error because the data records all attempted use of commands, independently of whether the command is valid or legitimate. This means that invalid transfer payments, such as attempting a payment that is of a value higher than a player's current balance, appears in the data no different from a valid transfer payment. It also makes it unreliable for the identifying when players choose to be randomly assigned, even though that choice is achieved through the use of a command called `rtp`. I explain how I identify randomly assigned players further in section 3.3. Nonetheless, I still make use of this data source to measure income under the assumption that players have nothing to gain from making mistakes in entering commands and thus, any and all invalid commands are equally likely to show up across potential treatment groups.

ChestShop Data. This comes from the ChestShop plugin and provides a record of shop creation (including private chestshops and AdminShops), price changes within each shop, and all purchases and sales made at every chestshop. Unlike the CoreProtect item data, the ChestShop data goes only from October 18, 2024 to January 17, 2025 (about three months).[6] Nonetheless, it provides real-time information on every market transaction in Stoneworks within that time frame. Combining this data with the CoreProtect item data, this provides the universe of how all items and resources flow between players in Stoneworks for a period of three months.

3.1.2 Map of Stoneworks

Since the real-time data only provides records of what the players do and not what the players' environment is like, I make use of a detailed high resolution map of Stoneworks Minecraft from shortly after the current iteration opened to the public in April of 2024 (Figure 2). This map gives me partial information as to the players' environment, though there are some obvious limitations.

[6] Author's note: I am in the process of trying to retrieve this data from the months past January.

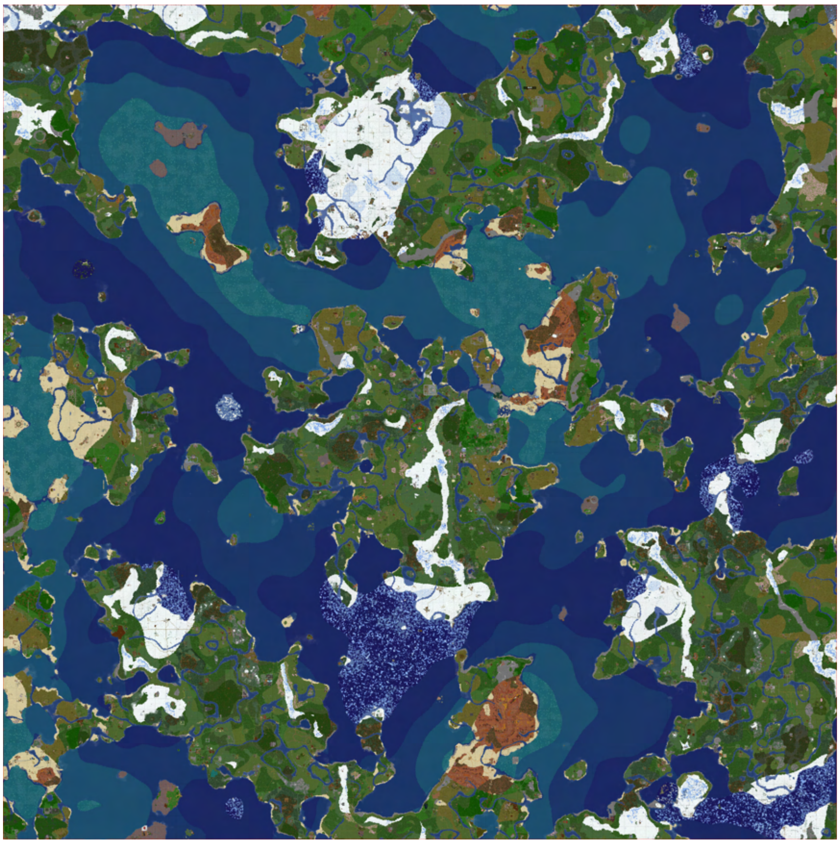

Figure 2: Map of Stoneworks Minecraft's current iteration as of April 2024, *Abexilas*.

The first is that the map is only two-dimensional and thus only shows the surface of the Stoneworks world. The second is that since the map is just a snapshot of the resource distribution present at the beginning of the game, it will surely inaccurately reflect the resource distribution players actually have available in my data since other players may have already extracted the resources identified within this map. Nonetheless, the map still provides valuable information for the analysis.

First and foremost, the map provides accurate information on all the biomes in Stoneworks and thus the likely resource distributions ex ante. Minecraft's procedural generation correlates many resources to particular biomes - for instance, wood is abundant in woodland biomes but scarce in deserts, pigs and sheep can be found in the plains and mountains, but not in snowy ones, and mushrooms are easier to find in wetland biomes but harder in arid ones. This allows me to control for the likely resource distribution when looking at features of players in an area so as to disentangle whether an effect is driven by the abundance, ecology, and available endowments of certain resources versus the attributes of the players.

The second benefit of using this map is that, because the map is from many months before the real-time data begins, the features in the map are completely exogenous to the randomly assigned locations and the behavior that arises from that random assignment. This is especially relevant in a game like Minecraft where players can destroy and place blocks, because it allows the possibility of players to do terraforming and change the distribution of blocks present on the surface. If I used a later map, like say one from the end of the study period in January (see Figure A6 in the Appendix), then there would be the problem that even if the random assignment provides exogenous variation in locations, the features of the future map would suddenly become "bad controls" because they are themselves endogenous and thus likely outcomes of the random location assignment that forms part of the experiment. A better alternative would be to have a dynamic map which provides accurate information about resources on the ground at the moment that players join the game, but for now we make do with what we have. At least by using the map from April, one gets both information about the biome and that information is exogenous to the economic behaviors of players.

3.2 Data Processing

I begin by aggregating the real-time data at the daily level so that I can compare together players who started within a similar time-frame. In order to keep an accurate account of an individual player's location over a particular day, I store each player's earliest and latest location 3D coordinate within the day from each real-time data source (session, item, command, and chestshop data), giving me at most eight locations per player per day (at most because if the player logs in and does nothing, then I would only get a login and logout location from the session data). I also construct four additional "in-between" locations based on the average over a player's recorded locations within a day, which means a maximum of twelve locations per player per day. Across 42,395 players over 286 days, this gives me a total of 550,175 individual-period observations and a total of 4,521,573 locations — this is markedly less than the maximum possible number of locations and the maximum possible of individual-period combinations because players do not play every day and also do not make use of all the recordable activities in the data.

The next step is to identify the groups which players belong to. Since nations and land claims can change day by day, the group of interest to me for an individual player is the group of players that cohabits the same area as the player of interest. In other words, the objective here is to find clusters of individual player locations over time. In this case, I use the player's average location coordinate as the representative within-day location of a player each period and use machine learning algorithms (Matt Piekenbrock and Claudia Malzer's `R` implementation of HDBSCAN (`hdbscan`) from Campello, Moulavi, and Sander, 2013) for identifying spatially clustered groups of players each day. Density-based spatial clustering of applications with noise (DBSCAN from Ester et al., 1996) algorithms and DBSCAN variants have been used in spatial analysis and urban economics in different contexts, including for delienating urban areas more accurately (Arribas-Bel, Garcia-López and Viladecans-Marsal, 2021), identifying clusters of crime, and clusters of similar socioeconomic attributes (Casali, Aydin, and Comes, 2022). One of the DBSCAN's strengths is that it can identify arbitrarily shaped clusters. I use HDBSCAN rather than the standard DBSCAN because HDBSCAN is capable of finding clusters of varying densities and does not rely on selecting a distance parameter, but rather only the minimum number of points necessary to define a cluster of points (in this case, I set the minimum number of points to 2). It also has been shown to outperform other non-parametric clustering algorithms. Over the entire game, I identify a total of 125,408 daily clustered groups of players - by construction, the groups have at least 2 players or more. The average number of groups per day is 446.89 (s.e. = 6.39) and the average number of players within a group is 3.003 (s.e. = 0.003), with the maximum number of players within a group being 28. These are the groups which I use to later measure wealth and income inequality.

Finally, I use k-means clustering to find clusters of similar pixel colors to identify the resources in the Stoneworks map from April. I set the number of possible clusters to 255. Then, I inspect each cluster manually by comparing the selected pixels in the map from April to a real-time 3D interactive map of Stoneworks available online, and check which blocks match the pixels, writing a brief description of each pixel cluster. I then classify each cluster based on my description of them into one of 14 block categories (dirt, farmland, grassland, ice, lava, mycelium, ocean, sand, snow, stone, structures, terracotta, and non-ocean water). The map of resources that results from this procedure is shown in Figure A5 in the Appendix.

Defining variables of interest. Since Minecraft does not directly measure income, expenses, or wealth, some choices need to be made as to how I define these important variables and this will obviously affect the resulting measure of inequality. Ideally, a player's income should reflect all the money that player receives within the game from all sources. A player can gain money automatically from sales in the player's chestshop, and periodically from received transfer payments from other players, and withdrawals the player can make from town coffers he/she has access to. The sales are directly observed from the ChestShop data, but the received transfers and withdrawals are imperfectly observed, since we see only the attempted transfer payments, tax payments, and tax collections, but not whether they are valid or not since that information comes from the command data. Nonetheless, I still use this data to define income but I address the measurement problem by using the median income as opposed to the average in the analysis (see section 3.4 for a justification as to why). For now, this means that the player's daily income is defined as

$$\text{Income}_{i,t} = \text{Sales}_{i,t} + \widehat{\text{Received Transfers}}_{i,t} + \widehat{\text{Collected Taxes}}_{i,t}.$$

For a variable x, I denote $\hat{x}$ as the attempted version of x observed in the command data. To measure daily expenses, I use an analogous accounting equation:

$$\text{Expenses}_{i,t} = \text{Purchases}_{i,t} + \widehat{\text{Sent Transfers}}_{i,t} + \widehat{\text{Tax Payments}}_{i,t}.$$

Finally, I define wealth as the cumulative sum of the difference between income and expenses, namely:

$$\text{Wealth}_{i,t} = \sum_{s=1}^{t} \left(\text{Income}_{i,t} - \text{Expenses}_{i,t} \right).$$

It is worth noting that because the money supply is effectively controlled by sales and purchases of items and resources to AdminShops (with sales increasing the money supply), this effectively conceals the informal economy that comes from material goods which are not transformed into money. In short, the measurable income and expenses is partially capped by AdminShop transactions, since the total supply of money is equal to the cumulative difference between sales to AdminShops (which transforms resources/items into money) and purchases from AdminShops (which transforms money back to resources).

In any case, in order for this paper to properly address the different literatures on the origins of inequality, we need to have analogous variables to those purported to be relevant for inequality - I discuss some of these papers at length in section 5, but nonetheless they have to be briefly addressed here.

There is a recent strand of literature in political economy that argues for appropriability of resources being a strong predictor for the rise of hierarchy and moreover, state capacity and the general enforcement of property rights (Mayshar, Moav, and Neeman, 2017; Mayshar, Moav, and Pascali, 2022; Huning and Wahl, 2023, Flückiger et al., 2024). In this literature, appropriability (or transparency, in the case of Mayshar, Moav, and Neeman's paper) is measured by the degree to which favorable farming conditions are observable through recurring climate trends, the relative productivity of crops which differ on their storeability, clustering in the caloric suitability of land. A broad definition of the appropriability concept is that an area is more appropriable if it is structurally easier for elites to extract revenue from that area.

While there are ways to introduce the type of variation in appropriability present in the literature within Minecraft, the data I have available simply does not include information on weather fluctuations and, in general, crops in Stoneworks Minecraft do not differ substantially in their suitability across biomes; the main elements necessary for land farming, soil and water, are generally abundant in the game. In lieu of this variation, I define a different measure: I'll consider an item appropriable if it can be stolen from a target player without the target being present in the act. This partitions food sources into appropriable and non-appropriable foods: for example, carrots would be considered appropriable because carrots can be stolen from a target player's farm without the target being there. Likewise, raw meats would also be considered appropriable since a player could kill a target player's farm animals without the target being there. However, a mushroom stew would be non-appropriable because a stew cannot be placed in Minecraft's environment and can only be stored within a player's inventory (or chest). The same applies to cooked meats, since once meats are cooked, they can only be contained within an inventory. Therefore, the only way to steal the mushroom stew or the cooked meat from a target player would be to attack the target player during a war to take their resources.[7]

Since much of the literature on historical inequality and appropriability relies on archaeological evidence, hierarchy has been measured in many different ways across different societies. Since we directly have access to income and wealth measures, we can directly calculate standard statistics of economic inequality. However, there is a distinction between economic inequality and jurisdictional hierarchy that would be valuable to disentangle since both measures intuitively ought to be correlated. To control for this, I can directly calculate the number of commands players use related to managing their lands as well as the number of commands players use related to managing a nation. Measuring state capacity is similarly straightforward: in this literature, it is typically measured by tax revenues and, since tax collection is already measured as income source, I need only keep track of the scale of incomes and the share of that income attributable to tax collection. The enforcement of property rights (or lack thereof) can also be measured by the number of land claims made in an area, with a high number of recent land claims being indicative of lower property rights.

Bowles and Fochesato (2024) (BF) argue that the cause of enduring inequality could have been "the introduction of farming technologies that raised the value of material wealth relative to labor." Their measure of this value increase is a society's capital intensity in food production, which is calculated by the elasticity share of capital inputs estimated by a constant returns to scale Cobb-Douglas production function. I measure capital intensity instead by the share of crafted items and items used in

[7]Another way of thinking about this appropriability definition is simply whether the item is placeable in the environment or not - items which cannot be placed and thus only stored within an inventory are non-appropriable whereas items which can be placed and thus stored outside an inventory are appropriable.

crafting relative to other forms of acquiring and using items (pickups, drops, sales, purchases), the assumption being that the act of using tools and inputs is inherently more capital intensive than not using them. The implication is that areas with high production of crafts relative to other items must therefore value material inputs (and therefore, material wealth) more than labor inputs. Throughout the paper, I will use the term capital intensive food and crafted foods interchangeably.

Finally, the most classical theories of inequality (Morgan 1877; Engels 1844) are that the emergence of economic surplus made possible by agriculture could have instrinsically generated high levels of inequality. In these classical theories, the possibility of long-term food surplus (i.e., food renewability) and dependence on land via agriculture is taken as one and the same. I disentangle these two channels by explicitly classifying foods in Minecraft as renewable or non-renewable separately from classifying them as land dependent or not. An item is considered renewable if it can be reproduced faster than it can be consumed; an item is considered land dependent if it requires irrigated dirt to be produced. In order to make different food sources comparable, I weigh each food by its caloric content (measured by sum of the number of food points and satiation each food source has, both of which are publicly available information). Table A1 provides a complete list of Minecraft's food sources and how I classify them based on appropriability, whether they are capital intensive, renewable, land dependent, and each food source's nutritional value.

Sample restrictions. Because of the discrepancy between the time window of the CoreProtect data (October 9 to July 15) and the time window of the ChestShop data (October 18 to January 17), I restrict the analysis from October 18 to January 17 so as to be able to measure income, expenses, and wealth (since sales and purchases rely on the ChestShop data). After processing the data, one can get a picture of the economic life in Stoneworks Minecraft in Figure 3. Section 4.1 documents properties of Stoneworks Minecraft's economy using the full dataset, including its aggregate indicators of growth and inequality as well as how correlations between key factors related to inequality map out in the data compared to what has already been found in the literature.

3.3 Random Assignment and Identification

The core exogenous variation is the choice of being randomly assigned a location. However, the choice of being randomly assigned is not perfectly observed because our data only shows "attempts" of random assignment as opposed to the actual event of random assignment, as I mentioned in section 3.1.1.[8] With this in mind, I use the universe of location data to back out successful random assignments of starting locations.

The basic idea is as follows: when players join an existing group of players, their starting location is effectively determined by the locations of other players. Therefore, it would be sufficient to conclude that a player's starting location is randomly assigned if their starting location was sufficiently far away from any player's history of locations. What follows is a formal description of the argument which then allows me to implement the solution in the data.

Let $\mathbf{L}_{i,t} \in \mathcal{L} \cup \emptyset$ be the location of player $i \in I$ at time $t > 0$, $\mathcal{L}$ be the set of possible locations, and I be the set of players, with the assumption that when $\mathbf{L}_{i,t} = \emptyset$, it must mean that player i is not in the game at time t. The shorthand $\mathbf{L}$ is a matrix of every player's location over time. Define $t_i^0 := \min\{t : \mathbf{L}_{i,t} \neq \emptyset\}$ as player i's starting location. If a player i selects into a location (i.e., joins an existing group of players), it should be that $\mathbf{L}_{i,t_i^0} \in N_r(\mathbf{L}_{j,s})$ for some non-empty $\mathbf{L}_{j,s}$, $j \in I, s \leq t_i^0$ where $N_r(\cdot)$ is a neighborhood of radius $r > 0$ around a location. When a player does not select into a starting location, it must mean that the player's starting location is randomly assigned. Therefore, a sufficient condition for being randomly assigned is that $\mathbf{L}_{i,t_i^0} \notin N_r(\mathbf{L}_{j,s})$ for any non-empty $\mathbf{L}_{j,s}$. In other words, the distance between $\mathbf{L}_{i,t_i^0}$ and any previous player's location at any period prior to t_i^0 should be greater than r. With this sufficient condition, I can define the distance from a player's location to the history of other players' locations as $D_{i,t} = \min_{j,s \leq t} ||\mathbf{L}_{i,t} - \mathbf{L}_{j,s}||_2$.

[8] Readers may wonder why random assignment should ever fail to occur. One of the main obstacles is that random assignment requires players to not move their avatar for a period of 15 seconds in order to happen. This is to make sure players do not accidentally randomly teleport to a different area of the map just because they accidentally typed in the command for random assignment to a location (`rtp`).

From this point on, I can partition the set of players into two subsets,

$$I_R(r) = \{i \in I : D_{i,t_i^0} > r\}, I_S(r) = I \setminus I_R(r).$$

Provided r is sufficiently large, the set $I_R(r)$ should only contain players with randomly assigned starting locations whereas $I_S(r)$ could still have both. For technical reasons related to the maximal distance a player could be from a hypothetical group of players one would join, I set $r = 2$ and omit the r parameter for the rest of the text.[9] With this partition, this allows me to use I_R as my study's sample because every player within that set was, for sure, randomly assigned their starting location.[10]

3.4 Causal Inference under Bundled Treatments

The operative research question of this paper is to understand the origins of persistent inequality. In an idealized experiment, the experimental design would be to randomly assign subjects to different environments (effectively, treatments) that vary only on the features that the literature claims ought to matter for the emergence of inequality and then compare the inequality that arises within each treatment group. In order to have enough power to do statistical tests, I would then need to repeat this experiment sufficiently many times to then estimate the effect that varying the features of interest had on the level of inequality within the treatment groups. Because of the assumption that the assignment is random, I get exogenous variation in the features of interest which ensures that any significant differences in the observed inequality between treatment groups is attributable to the design of the experiment. And because of the assumption that I *only* varied the relevant

[9] When players set starting locations for new players to join their groups, it is set at the coordinate level so, in theory, r should be zero. However, because there can be latency between when a player joins the game and when CoreProtect records that a player joins the game, it's possible that at the moment when a player joins, they have moved from their location and thus the recorded r is greater than zero. This then means that you could have players which selected their location but end up having a distance greater than r if r is small. The sprinting speed in Minecraft is about 7.127m/s and, as a general norm, players (and companies) tend to avoid playing first-person games with real-time feedback with latencies greater than 300ms. Therefore, the maximum distance a player could travel within that acceptable latency between when a player starts and the game records them starting is 2.13 meters. Since coordinates are measured by the nearest cubic meter, this rounds down the maximum distance to 2.

[10] One natural question would be how this sample of players differs from I_S. I discuss this briefly in section D of the Appendix.

features, I am able to identify which of the features are responsible for the significant differences in observed inequality between the treatment groups.

However, as is often the case with applied work and natural experiments, sometimes it is difficult to get both exogenous variation and identification at the same time. The random assignment of location ensures that, on average, players are ex ante identical in their expected outcomes, so that any systematic differences observed between players starting in different areas can be attributed to the characteristics of those locations rather than to player selection. However, each starting location bundles many relevant features for institution formation—such as geography, resource composition, and exposure to existing groups—making it difficult to isolate which specific feature drives the observed differences in outcomes. For example, estimating the effect of starting near a desert by regressing outcomes on proximity to a desert may be misleading if desert areas are also correlated with food scarcity or with exposure to players belonging to nomadic cultures. In practice, players are simultaneously exposed to multiple bundled treatments, which complicates the identification of the causal feature responsible for an effect. In summary, the issue is that bundled treatment creates the possibility of omitted variable bias and potentially attributing a treatment effect to an irrelevant variable.

To address this more formally, let $\left(f_s(\mathbf{L}_{i,t})\right)_{s=1}^{K}$ be the vector of K real-valued location features for location $L_{i,t}$ at period t (as an abuse of notation, I omit the time argument from f and always assume the features correspond to the location's features at the denoted subscript of the period). To estimate the partial effect of each randomly assigned location feature, I estimate the following regression specifications:

$$\text{Outcome}_{i,t} = \beta_0 + \sum_{s=1}^{K} f_s\big(\mathbf{L}_{i,t_i^0}\big)\beta_s + \eta_{t_i^0,t} + \epsilon_{i,t}, i \in I_R,$$

$$\begin{aligned}\text{Group Outcome}_{g,t} = \gamma_0 &+ \frac{1}{|g \cap I_R|} \sum_{i \in g \cap I_R} \sum_{s=1}^{K} f_s\big(\mathbf{L}_{i,t_i^0}\big)\gamma_s \\ &+ \frac{1}{|g|} \sum_{i \in g} \mathbf{1}\{i \in I_R\}\delta_R + \eta_{t,\min_i\{t_i^0 : i \in g\}} + \varepsilon_{g,t}.\end{aligned}$$

The outcome of interest will typically be income and wealth inequality, but I will also consider other outcomes such as income and wealth levels at the individual level; I denote an individual by i and a group by g with the abuse of notation that g also represents the set of players denoted by the group g. At the group level, I again use Driscoll and Kraay standard errors; at the individual levels, I partition the coordinate space of players into 400m $\times$ 400m grid cells and cluster the standard errors at the user-starting-grid-cell level to match the fact that players are randomly assigned at the individual level to a location. When the features are randomly assigned, β_s can be intepreted as the average change in a player's outcome caused by a one-unit increase in feature s in a player's starting location, all else fixed. In the group setting, γ_s can be interpreted as the average change in a group outcome caused by a one-unit increase in the average of feature s across the I_R group members' starting locations, all else fixed.[11]

In principle, only the features related to theories of how inequality emerges should be important/relevant to me (e.g., the number of players present in a starting location, whether the production is capital-intensive or renewable, the existing level of wealth and income inequality, to name a few); one can denote the set of relevant features as $S^* \subset \{1, \ldots, K\}$ and the set of irrelevant features as $S^c = \{1, \ldots, K\} \backslash S^*$. Random assignment of locations induces a distribution over $\mathbb{R}^K$ in which some irrelevant features may be correlated with relevant features (e.g., farmland in a starting location's surface will be correlated with land-dependent production). By including a large set of features, many of which are potentially irrelevant, I can reduce the chances of having unobserved confounders (i.e., omitted variable bias), which will improve my odds of identifying the treatment effect. With this strategy, the key identification assumption is that the random assignment only affects outcome variables through the location features included in the regression (in other words, there are no unobservable confounders).

This strategy comes at a cost of finding spurious correlations, since increasing the number of location features increases the probability of at least one false positive

[11]Because of the measurement error introduced by only having recorded attempts as opposed to final outcomes in the data (as is the case with taxes and transfers), the median is sometimes used in lieu of the average. If the mis-measured variable is bounded between zero and one, I use the average whereas if the mis-measured variable is unbounded, I use the median.

result. To control for this, I use Romano and Wolf's (2016) multiple hypothesis corrections to calculate multiple test adjusted p-values; these resampling techniques controls the familywise error rate and is known to have greater power than other techniques for multiple hypothesis corrections (e.g. Bonferroni (1935), Holm (1979), and Benjamin and Hochberg (1995), for example) by incorporating information about the joint dependence structure of test statistics (List et al., 2023).

Feature set For all players identified as randomly assigned according to I_R, I consider a 200m (or 100 pixel) radius ball surrounding the player's starting location coordinate to calculate each player's starting location's features.[12] These features can broadly be split into two categories: environmental features (of which there are 13) and user-driven features (of which there are 80). The full list of location features is in Section C in the Appendix.

The environmental features all use information from the resources map in Figure A5. For every starting location, I calculate the proportion of every resource on the surface to control for the resource distribution available to a player. As previously mentioned, this map is merely a snapshot of the resouce distribution present prior to the study period, but it still provides useful information of the resources players are expected to encounter. The user-driven features are primarily averages of the outcomes of players surrounding a starting location; to avoid the individual player having an influence on that average within the day, I calculate one-day lagged average player outcomes for players surrounding a starting location. The assumption is that user-driven features are unlikely to change from one day to the next.

The most important location features included in the analysis are:

1. **Lagged average share of food gain in capital-intensive, appropriable, renewable, and land dependent foods of players surrounding a randomly assigned starting location.** This allows me to compare players exposed to different modes of food production to estimate the partial effect of

[12] Author's note: how much a player in Minecraft perceives in 3D space depends on their computer, but the default render distance (meaning, how far away the player can see from where they stand) is 8 chunks for 32-bit computers and 12 chunks for 64-bit computers. A chunk is a rectangular area of 16 by 16 cubic meters going from maximum to minimum height. Since Stoneworks Minecraft is only available on the Java edition of Minecraft, this makes the default perceivable distance a maximum of 192m. It would be useful to verify whether the results of the paper are robust to different radiuses.

particular food attributes as MMP and BF do.

2. **Lagged average level of food gain of players surrounding a randomly assigned starting location.** This allows me to control for the level of food gained by players to disentangle the composition of food from the surplus of food.

3. **Lagged average share of income (expenses) in tax collection (payments) of players surrounding a randomly assigned starting location.** This allows me to compare players exposed to different levels of state capacity so as to estimate its partial effect, as Boix (2010) and Acemoglu and Robinson (2012) suggest was the channel that allowed appropriability to generate long-term differences in inequality.

4. **Lagged average level of income, expenses, and wealth of players surrounding a randomly assigned starting location.** This allows me to control for the size of the local economies to disentangle state capacity variables from income and wealth.

5. **Lagged average within-group Gini coefficient of income and wealth of players surrounding a randomly assigned starting location.** This allows me to compare players exposed to high versus low inequality communities in order to estimate whether players replicate or counter existing levels of inequalities; Graeber and Wengrow (2021) argue for "aggressive egalitarianism" being the default, which means that players' social preferences ought to avoid replicating high levels of inequality where possible.

4 Results

In this section, I start by giving documenting the economy of Stoneworks in section 4.1 and providing descriptive evidence for how inequality is correlated with different factors. Then, I showcase the results of estimating the baseline specification described in Section 3.4, starting with how wealth and income inequality are affected by a features of randomly assigned starting locations in Section 4.2. The main result is that the composition of food sources of players' food production surrounding a randomly assigned starting location has a significant effect on income and wealth inequality. In Section 4.3, I decompose the main results further to identify which food attributes, if any, are responsible for the effect.

4.1 The Stoneworks Economy in Numbers

On any given day, more than a thousand players log into Stoneworks with strong weekly seasonality attributable to players being more active over the weekend (see Figure 3).[13] Over the nearly three months that I observe, user activity and economic growth in the form of GDP and GDP per capita does not see any extreme changes as the economy's trends are consistent with a roughly balanced growth path: if measured at an annual rate, GDP is growing at 2.13% (1.42% per-capita) on average (s.e. = 0.94%, 0.85% per-capita), wealth is growing at an average rate of 10.93% (11.12% per-capita) (s.e. = 0.62%, 0.68% per-capita), and the number of active users decreases at a non-significant rate of 0.19% (s.e. = 0.19%). The average time per session does decrease significantly by 0.47% (s.e. = 0.16%), with comparable decreases in the total person-hours (on average, 0.57%, s.e. = 0.32%). Finally, income and wealth inequality between all players is relatively high (greater than 0.60 for income and greater than 0.90 for wealth), with comparably lower within-group inequality (less than 0.10 for income, less than 0.65 for wealth).

Given the levels of wealth and income inequality both overall and within groups, it is clear that players differ substantially in how much income and wealth they generate. Figure 4 shows the distribution of daily income, expenses, wealth, and wealth truncated at zero pooled over all periods.[14] A natural question is what makes higher income/wealth players different from the others. Figure 5 shows the (correlational) relationship between income sources, expenditures, and a player's percentile in income, expenses, and wealth (again, pooled over all periods). Whereas high percentiles in income (expenditures) are correlated with a high share of income (expenses) from sales (purchases) and transfer payments, high percentiles in wealth

[13] When calculating wealth inequality, negative values are truncated to zero to keep the Gini interpretable between zero and one.

[14] Because of the high counts of zeroes, the shape of the histogram has been transformed so as to make the rest of the distribution more visible. The undistorted histogram is in Figure A10, with a cumulative sum per user version in Figure A11. For versions scaled in inverse hyperbolic sine, see Figure A12 and A13 in the Appendix.

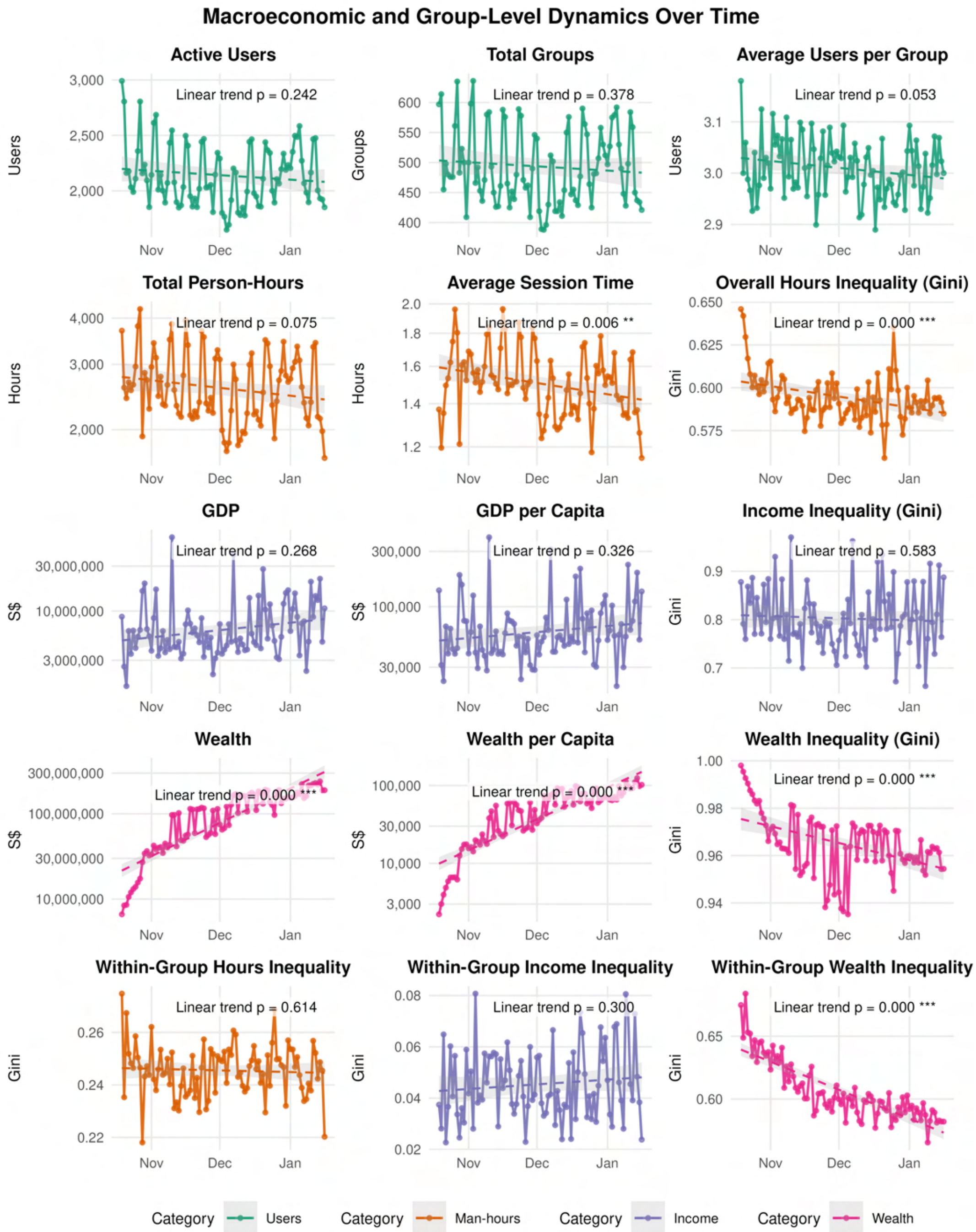

Figure 3: Time series of macroeconomic variables in Stoneworks from October 18, 2024 to January 17, 2025 at the daily level. Money variables are measured in Stoneworks coins (S$) and shown in logarithmic scale. Groups are identified by finding spatially clustered players within a day using HDBSCAN. High volatility is driven by transitions in and out of the weekends.

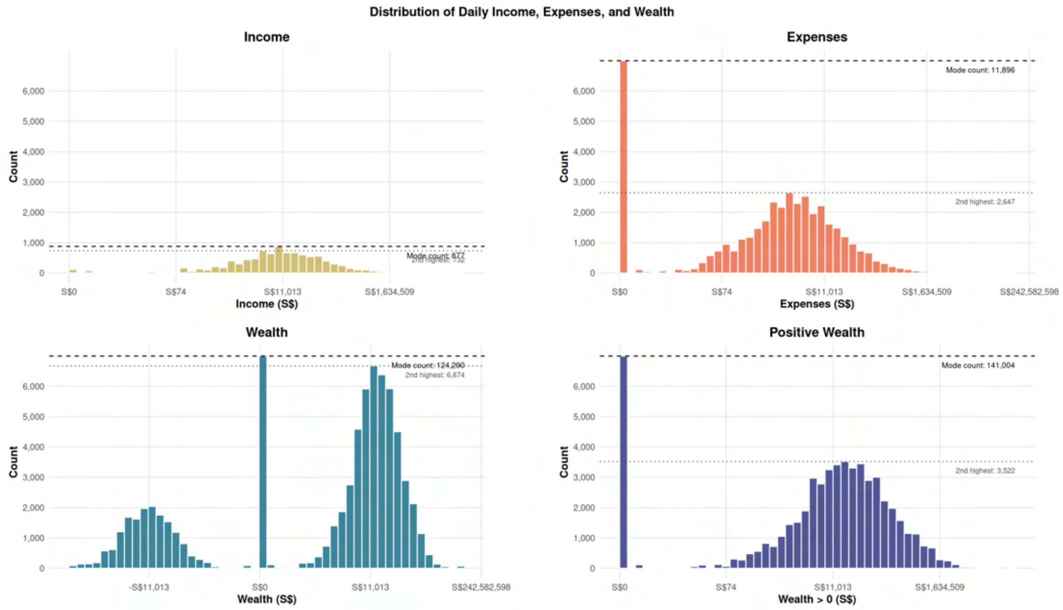

Figure 4: Histograms of user-period income, expenses, wealth, and wealth truncated at zero. The mode of the distribution (labeled in long dashed line) is not drawn at scale in order to make the rest of the histogram visible. The histograms with the modes drawn at scale can be seen in Figure A10.

are associated with tax collection and payments.

These differences in composition of income and expenses exhibit different degrees of persistence over time. I estimate non-parametrically the conditional expected shares of income sources and expenditure as a function of past period shares using Hastie and Tibshirani's (1986) GAM estimator, the results of which are shown in Figure 6. The average share of income from transfer payments is 60% (median = 80%, s.e. = 0.41%) whereas the average share from sales is 30% (median = 10%, s.e. = 0.39%). By contrast, the average share from tax collection is 10% (median = 0%, 0.22%); over the entire study, only 14.93% of users collect taxes from other players. With regards to expenditures, the average share from purchases is 70% (median = 100%, s.e. = 0.22%), which makes the vast majority of expenses from chestshops.

Given the existence of markets in Stoneworks, it is plausible that much of the exchange and production of food could happen in the market. This could threaten my ability to study how food composition affects early economic development, especially the transition from hunter-gathering to stable food production from agriculture — for instance, if it turned out that players regularly source their food by buying from relatively few food sellers, then this could crowd out local production and gathering

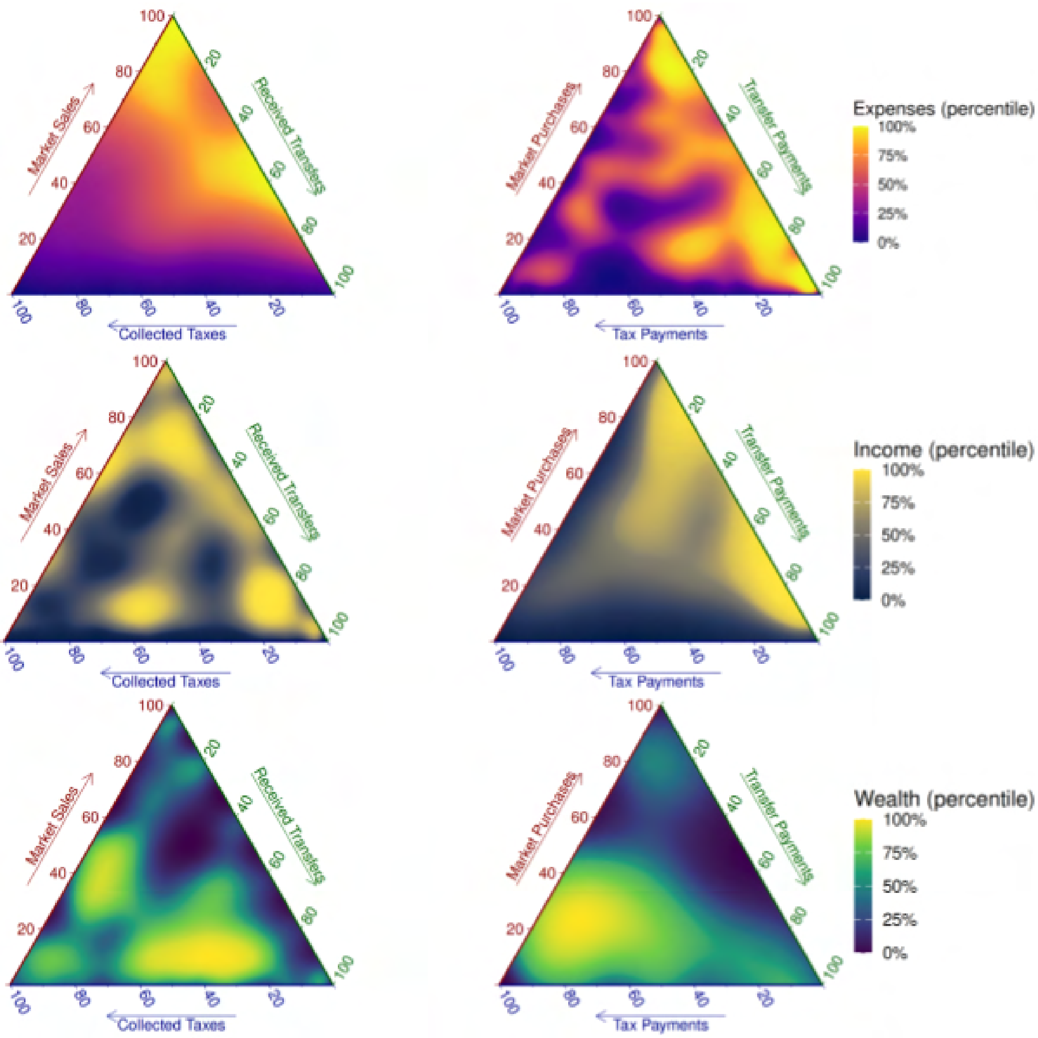

Figure 5: Composition of income and expenses and how they affect income, expense, and wealth percentiles. The top always of the ternary always corresponds to an income/expense distribution driven fully by market transactions, the bottom-left driven fully by tax payments/collection, and bottom-right by transfer payments. The area of each ternary plot is colored according to average percentile conditional on composition (estimated using GAM smoothing functions).

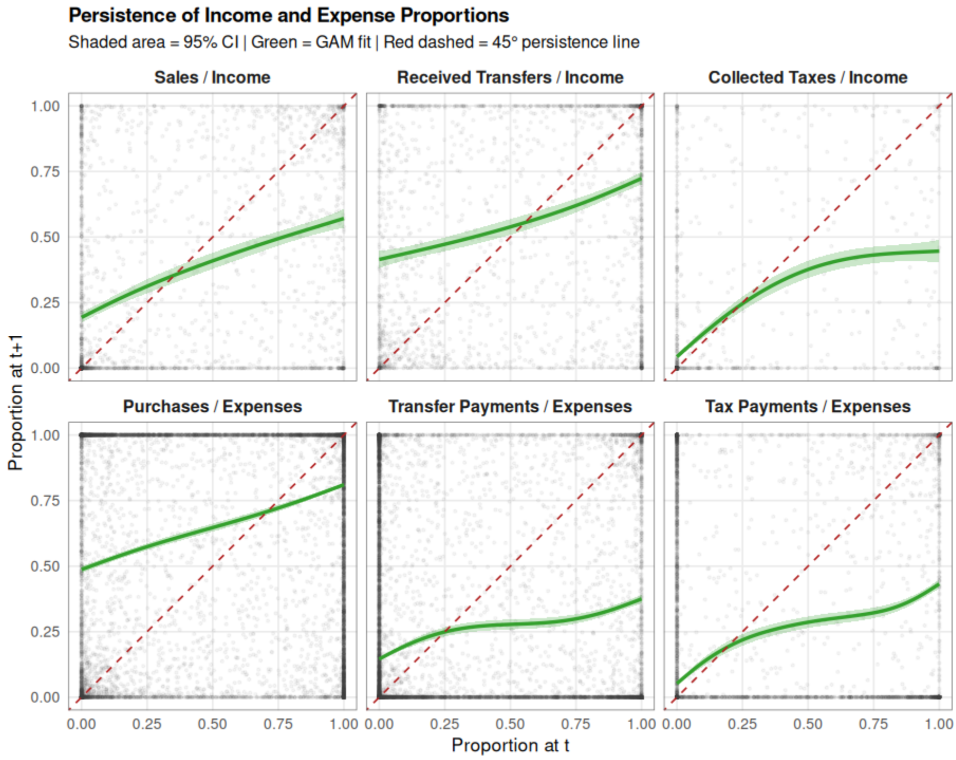

Figure 6: Expected shares of income sources and expenditure sources, conditional on past period shares, estimated using GAM. The red dashed 45-degree line corresponds to the expected share at $t + 1$ being equal to the share at t.

of foods, which would then lead to insufficient variation for studying the relationship between local food composition and inequality.

Thankfully, this is not the case. I repeat the same exercise for income and expenses with how players obtain and use food in Figure 7. The vast majority of food is persistently obtained by players either gathering food directly from the environment or picking it up from other players (average share of 90%, median = 100%, s.e. = 0.07%). Despite the fact that most expenditures are spent on purchases, the average share of food obtained through purchases is remarkably low (2%, median = 0%, s.e. = 0.03%). Finally, the average share of food obtained through crafting is 14% (median = 0%, s.e. = 0.07%); similarly to tax collection, food producers also make up a sizeable minority of players, with only 33.91% of users crafting food over the entire study.

Food Sources, State Capacity, and Inequality After decomposing food sources based on the method of acquisition and use, whether the foods are appropriable, and whether they are renewable and/or land-dependent, one can get a view as to the

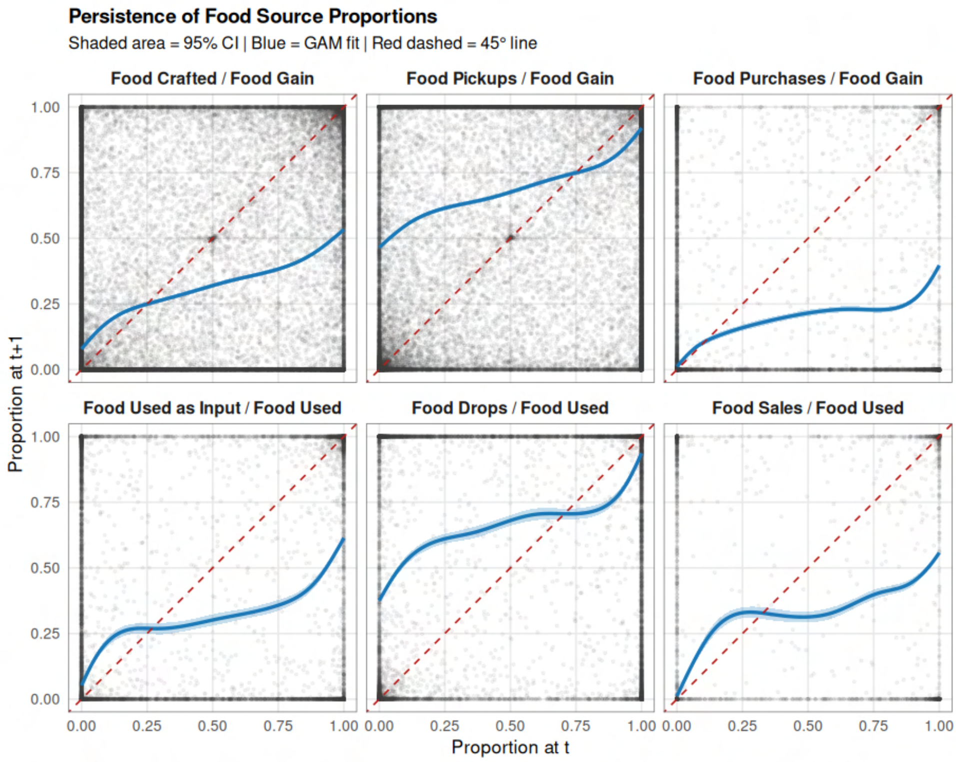

Figure 7: Expected shares of food sources in food gain and food use, conditional on past period shares, estimated using GAM. Food is measured in nutritional value. The red dashed 45-degree line corresponds to the expected share at $t+1$ being equal to the share at t.

aggregate diet composition in Stoneworks Minecraft (see Figure 8 and Figure 9).

The production of food in Stoneworks consists of many different food sources which are used differently. Since food pickups are acquired either by gathering directly from the environment or picking up food from either players' drops, food pickups are a measure for the supply of raw food (i.e., food prior to being used as a crafting input for other food/items) that players acquire outside of the market system. Because of this, one can infer the (correlational) relationship between appropriability, renewability, and land-dependence on food use and production by comparing the composition of food sources in pickups to the composition of food sources in other modes of acquisition and use.

Of the 90% of food production that is acquired through pickups, there is an almost half-and-half split between appropriable (49%) and non-appropriable (51%) foods. There is a similar split between land dependent foods and non-land dependent foods. Renewable foods make up the vast majority of food production and food use out-

Figure 8: Treemaps of food production and food use. Food surplus is defined as the difference between food production and food use. Within each cell is the total number of nutritional value generated by category of food source. Land-dependence and lack thereof is reported as "Farm" and "Non-Farm" respectively.

Food Crafted

Farm	Renewable	Nonrenewable
App	0.07	0.00
Non-App	0.86	0.03

Non-Farm	Renewable	Nonrenewable
App	0.01	0.00
Non-App	0.00	0.03

Food Pickups

Farm	Renewable	Nonrenewable
App	0.24	0.00
Non-App	0.28	0.00

Non-Farm	Renewable	Nonrenewable
App	0.25	0.00
Non-App	0.07	0.16

Food Purchases

Farm	Renewable	Nonrenewable
App	0.13	0.00
Non-App	0.57	0.00

Non-Farm	Renewable	Nonrenewable
App	0.09	0.00
Non-App	0.15	0.05

Food Used as Input

Farm	Renewable	Nonrenewable
App	0.51	0.00
Non-App	0.00	0.00

Non-Farm	Renewable	Nonrenewable
App	0.32	0.00
Non-App	0.00	0.17

Food Drops

Farm	Renewable	Nonrenewable
App	0.17	0.00
Non-App	0.51	0.00

Non-Farm	Renewable	Nonrenewable
App	0.13	0.00
Non-App	0.07	0.12

Food Sales

Farm	Renewable	Nonrenewable
App	0.46	0.00
Non-App	0.19	0.00

Non-Farm	Renewable	Nonrenewable
App	0.20	0.00
Non-App	0.08	0.07

Figure 9: Proportion of food attributes by method of gaining/using food. App is short for "appropriable", land-dependence and lack thereof is reported as "Farm" and "Non-Farm" respectively.

right, making up 84% of food pickups, but also 83% of food inputs, 88% of food drops, 93% of food sales, 94% of food crafted, and 95% of food purchases.[15] In other words, throughout every stage of how food is used in the game after initial pickup (outside of consumption, which is unobservable in my data), non-renewable (renewable) foods become less (more) prevalent.

A similar pattern emerges when I compare land dependence. Land dependent foods make up 51% of food inputs, 65% of food sales, 68% of food drops, 70% of food purchases, and 96% of food crafts. After initial pickup, food becomes more land dependent at every stage of food production. However, this pattern of increasing (or decreasing) prevalence does not apply to appropriable foods. While appropriable foods make up 49% of food pickups, they are widely used as food inputs (83%) and food sales (66%) but less used as food drops (30%), less likely to be purchased (22%) and rarely the outcome of crafting (8%). In other words, whereas renewability and land dependence are food attributes that become more prevalent after initial pickup, appropriability is an attribute that is associated with specific modes of food use and production.

What is the relationship between these food attributes and inequality? I estimate the average within-group Gini for income and wealth, conditional on each food attribute at a time in Figure 10. Groups with a greater share of renewable food gain have a small but significant positive difference in income and wealth inequality; the same applies for capital intensity and land dependence. However, it is important to note that these food attributes are not independent, which means that the correlation between inequality and say, renewability, might be misleading if renewability is highly correlated with land dependence, for example.

[15]Some readers might be drawn as to why food sales are not equal to food purchases. Sales and purchases are measured at the individual player level and then aggregated, which means that the difference between aggregate sales and purchases is from AdminShops. To see this more clearly, consider the identities $\text{Sales}_{i,t} = \text{AdminSales}_{i,t} + \text{UserSales}_{i,t}$ and $\text{Purchases}_{i,t} = \text{AdminPurchases}_{i,t} + \text{UserPurchases}_{i,t}$. Since these are user-period observations, I am distinguishing between transactions done at admin shops (in which case, there is no player at the other side of the transaction) and transactions done at player chestshops. Of course, there is a market clearing condition with relation to player chestshops that requires $\sum_i \text{UserSales}_{i,t} = \text{UserPurchases}_{i,t}$, but no such requirement exists for AdminShops because the AdminShop is not run by a player and thus operates outside of the resource gathering economy. Therefore, you have that $\sum_i \left(\text{Sales}_{i,t} - \text{Purchases}_{i,t}\right) = \sum_i \left(\text{AdminSales}_{i,t} - \text{AdminPurchases}_{i,t}\right)$. This difference, by the way, is identically equal to the money supply in Stoneworks since money is created through sales at AdminShops and depleted by purchases at AdminShops.

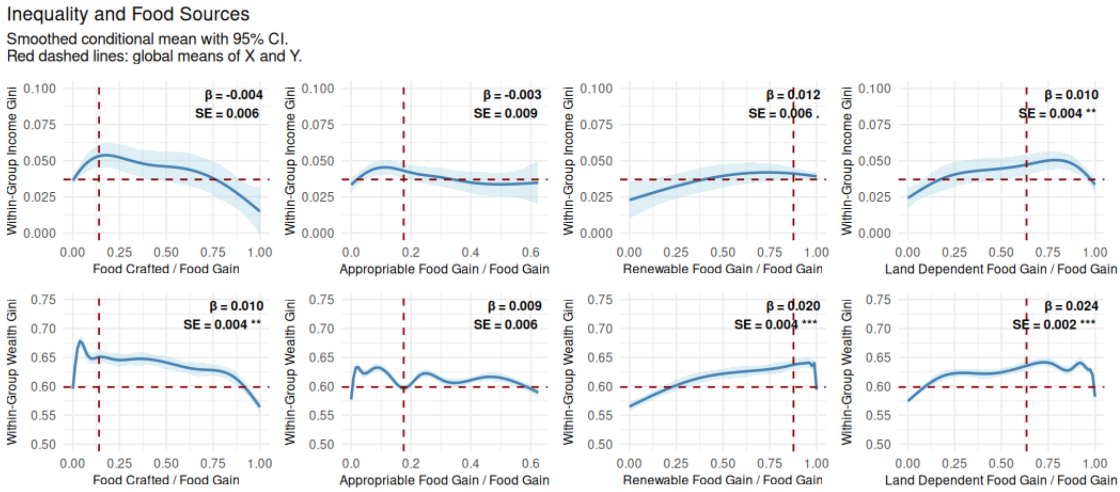

Figure 10: Expected income and wealth Gini, conditional on food source proportions, estimated using GAM. Food is measured in nutritional value. The red dashed lines are the means for their respective axes (the vertical line being for the food source proportion, the horizontal line for the Gini).

In Table 1, I calculate the pairwise correlation between the share of each attribute in acquiring food at the period-group level. Renewability and land dependence are positively correlated (as I hinted earlier), whereas capital intensity and appropriability are negatively correlated. Since the share in each attribute is endogenous, I also calculate the pairwise correlation between these factors in all the existing food sources, weighing each equally, in Table 2; in effect, this table represents the correlation in these food attributes according to the game design of Minecraft as opposed to what players do in the game. Both Table 1 and Table 2 illustrate not only that the food attributes are correlated, but also the relative compatibility of different theories as to how the production technology of food can come and affect inequality. Since none of the food attributes are close to perfectly correlated, it is possible to consider how different (pairwise) combinations of these attributes in food production can lead to differences in economic outcomes. In order to disentangle the correlation between these food attributes and better understand their contributions to inequality, I estimate the following regression specification:

Table 1: Pairwise Correlations Between Food Attributes in Food Gained

	Capital	App	Renew	Land
Capital	1.000			
App	-0.249^{***}	1.000		
Renew	0.122^{***}	0.024^{***}	1.000	
Land	0.277^{***}	-0.054^{***}	0.520^{***}	1.000

Notes: Table reports Pearson pairwise correlations between the share of food gain from crafted foods (Capital), the share from appropriable foods (App), the share from renewable foods (Renew), and the share from land-dependent (Land). The shares are all calculated at the group-level. Stars denote significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 2: Pairwise Correlations Between Food Attributes in All Foods

	Capital	App	Renew	Land
Capital	1.000			
App	-0.707^{***}	1.000		
Renew	0.606^{***}	-0.256^{***}	1.000	
Land	0.064^{***}	0.108^{***}	0.270^{***}	1.000

Notes: Table reports Pearson pairwise correlations between foods being craftable (Capital), appropriable (App), renewable (Renew), and land dependent (Land). This can be calculated by hand using Table A1. Stars denote significance levels, confidence intervals are calculated using bootstrapping (randomly sampling food sources with replacement): $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

$$
\begin{aligned}
\text{Inequality}_{g,t} = {} & \beta_{\text{Capital}}\left(\frac{\sum_{i\in g}\text{Food Crafts}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) + \beta_{\text{App}}\left(\frac{\sum_{i\in g}\text{Appropriable FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \\
& + \beta_{\text{Renew}}\left(\sum_{i\in g}\frac{\text{Renewable FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) + \beta_{\text{Land}}\left(\frac{\sum_{i\in g}\text{Land Dep. FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \\
& + \beta_{\text{Capital}\times\text{App}}\left(\frac{\sum_{i\in g}\text{Food Crafts}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \times \left(\frac{\sum_{i\in g}\text{Appropriable FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \\
& + \beta_{\text{Capital}\times\text{Renew}}\left(\frac{\sum_{i\in g}\text{Food Crafts}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \times \left(\frac{\sum_{i\in g}\text{Renewable FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \\
& + \beta_{\text{Capital}\times\text{Land}}\left(\frac{\sum_{i\in g}\text{Food Crafts}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \times \left(\frac{\sum_{i\in g}\text{Land Dep. FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \\
& + \beta_{\text{App}\times\text{Renew}}\left(\frac{\sum_{i\in g}\text{Appropriable FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \times \left(\frac{\sum_{i\in g}\text{Renewable FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \\
& + \beta_{\text{App}\times\text{Land}}\left(\frac{\sum_{i\in g}\text{Appropriable FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \times \left(\frac{\sum_{i\in g}\text{Land Dep. FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \\
& + \beta_{\text{Renew}\times\text{Land}}\left(\frac{\sum_{i\in g}\text{Renewable FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \times \left(\frac{\sum_{i\in g}\text{Land Dep. FG}_{i,t}}{\sum_{i\in g}\text{Food Gain}_{i,t}}\right) \\
& + \alpha + \eta_{t,\min_i\{t_i^0 : i\in g\}} + \delta'\mathbf{X}_{g,t} + \epsilon_{g,t}.
\end{aligned}
$$

where $\text{Inequality}_{g,t}$ is a Gini coefficient measure for group g in period t, $\text{Food Gain}_{i,t}$ is the sum (in nutritional value) of food pickups, crafts, and purchases for player i in period t, $\text{Appropriable FG}_{i,t}$ is the sum of food pickups, crafts, and purchases from only appropriable food sources, $\text{Renewable FG}_{i,t}$ from only renewable food sources, and $\text{Land Dep. FG}_{i,t}$ from only land dependent food sources. In the case of the wealth Gini, I truncate wealth at zero from below to ensure the Gini coefficient stays interpretable between zero and one. The age of a group is represented by the earliest starting period within a group, $\min_i\{t_i^0 : i \in g\}$, so that $\eta_{t,\min_i\{t_i : i\in g\}}$ represents a cohort (or tenure-period) fixed effect. $\mathbf{X}_{g,t}$ is a vector of group-level controls which I will vary according to the inequality measure (using the inverse hyperbolic sine (IHS) of total group income for the income Gini, IHS of total group wealth for the wealth Gini, and IHS of total food gain for both). Finally, I use Driscoll and Kraay (1998) robust standard errors to account for serial dependence across periods and use Romano and Wolf's (2016) multiple hypothesis corrections to calculate multiple test adjusted p-values. Table 3 reports the results of estimating variants of the above regression specification (specifically, with and without the interaction terms).

Since this is simply regressing inequality on these food attributes' share of food gain, both of which can be endogenous, I cannot use these coefficient estimates to conclude anything more than a suggestive partial correlation between inequality and the independent variables included in the regression. Nonetheless, it is important to understand how the coefficient estimates line up with existing theories of how these factors affect the emergence of inequality.

For instance, Mayshar, Moav, and Pascali (2022) (MMP) find a positive correlation between appropriability, land productivity, and hierarchy;[16] at the same time, MMP find that if both appropriability and land productivity are included as covariates in a regression estimation for hierarchy, the partial correlation between land productivity and hierarchy statistically disappears.[17] I find an analogous (but less significant) result in my regression estimates, with $\hat{\beta}_{\text{App}} \geq \hat{\beta}_{\text{Land}} \geq 0$ for all specifications and β_{App} having a significant and positive coefficient estimate when wealth inequality is the dependent variable and there are no interaction terms.[18] In Table A2 in the Appendix, I also find that the result holds even without controlling for renewable and capital-intensive foods. [19]

Bowles and Fochesato (2024) (BF) find a positive correlation between capital intensity and wealth inequality. While I do find a small positive correlation between capital intensity outright and wealth inequality (see the coefficient for crafted foods in Figure 10), the relationship between capital intensity and inequality in Stoneworks Minecraft is not as clear cut. When I control for shares of food gain in appropriable, renewable, and land-dependent foods, the coefficient estimate for β_{Capital} does not appear to significantly differ from zero. Moreover, the interaction between capital

[16]Appropriability is measured by the reliance in cereal grains for a society's subsistence, the idea being that societies which rely on cereal grain have a greater relative appropriability than societies which rely on, say, tubers. Land productivity is measured by the potential caloric yields in an area. Hierarchy is measured using ethnographic data on jurisdictional complexity beyond local community, with low levels of hierarchy corresponding to zero political authority beyond the community whereas high levels correspond to living underneath a state.

[17]MMP's regression includes a large battery of controls, including period and continent fixed effects as well as different geographic features. Importantly, their regression does not include an interaction term between land productivity and appropriability.

[18]The short-hand $\hat{\theta}$ is used to refer to an estimate of some parameter θ.

[19]Editor's note: it would be good to know what is the relationship between hierarchy if one includes an interaction term between land productivity and appropriability using MMP's replication files/dataset.

Table 3: Within-Group Inequality and Food Sources

	Income Gini (1)	Income Gini (2)	Wealth Gini (3)	Wealth Gini (4)
β_{Capital}	-0.004	-0.039	0.010	-0.022
	(0.006)	(0.022)	(0.006)	(0.025)
β_{App}	0.008	-0.035	$0.018^{*,r}$	0.047
	(0.008)	(0.061)	(0.009)	(0.038)
β_{Renew}	-0.004	-0.003	-0.006	-0.001
	(0.007)	(0.014)	(0.006)	(0.010)
β_{Land}	0.004	$0.097^{**,r}$	0.005	$0.238^{***,rrr}$
	(0.005)	(0.032)	(0.004)	(0.023)
$\beta_{\text{Capital}\times\text{App}}$		0.104^{***}		0.031
		(0.030)		(0.081)
$\beta_{\text{Capital}\times\text{Renew}}$		0.057		$0.152^{***,rrr}$
		(0.041)		(0.033)
$\beta_{\text{Capital}\times\text{Land}}$		-0.032		$-0.132^{***,rrr}$
		(0.037)		(0.023)
$\beta_{\text{App}\times\text{Renew}}$		0.046		0.041
		(0.067)		(0.042)
$\beta_{\text{App}\times\text{Land}}$		-0.010		$-0.089^{***,rrr}$
		(0.026)		(0.021)
$\beta_{\text{Renew}\times\text{Land}}$		$-0.093^{**,r}$		$-0.218^{***,rrr}$
		(0.033)		(0.022)
Cohort FEs	Yes	Yes	Yes	Yes
Decomposed Food	No	No	No	No
Controls	Yes	Yes	Yes	Yes
Interactions	No	Yes	No	Yes
Observations	6,808	6,808	22,304	22,304
Cohorts	960	960	2,010	2,010
Minimum groups per period	35	35	64	64
Median groups per period	69	69	252	252
Maximum groups per period	143	143	386	386
R squared	0.178	0.180	0.145	0.151
Mean dep. var.	0.039	0.039	0.608	0.608

Notes: The table presents results from regressions of the within-group Gini coefficients of spatially clustered groups in a day (by HDBSCAN) on the share of food gain from crafted foods (Capital), the share from appropriable foods (App), the share from renewable foods (Renew), the share from land-dependent foods (Land), and interactions of those food shares in the same day. Controls include the inverse hyperbolic sine (IHS) of total group income for the income Gini, the IHS of total group wealth for the wealth Gini, and IHS of total food gain for both. Standard errors are robust to serial dependence (Driscoll and Kraay, 1998), Romano-Wolf p-value adjustment accounts for hypothesis testing in Table 6 and Table 5.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
(Romano-Wolf Adjusted: ^{r} $p^{RW} < 0.05$, ^{rr} $p^{RW} < 0.01$, ^{rrr} $p^{RW} < 0.001$).

intensity and other food attributes can result in significantly different estimated levels of income and wealth inequality. While this would appear to be at odds with BF's main hypothesis, they argue that capital intensity was a necessary condition among many in the rise of enduring wealth inequality: "[f]irst... sedentary living along with harvesting and then cultivating storable cereals ... provided opportunities for private ownership of ... the sources of livelihood ... Moreover the increasingly storable nature of the goods making up a ... livelihood along with private ownership of stores allowed the more successful households to withdraw from community-based risk-mitigation practices by means of private storage, reducing the extent of egalitarian redistribution... Second... capital-intensive labor-saving methods of production ... increased the value of forms of wealth ... that, unlike the capacity to perform labor, could be very unequally held ... Third... the gradual centralization of the effective use of coercion ... mitigated the likelihood of ... challenges to wealth holdings of the elite ... thereby providing the political conditions for enduring wealth inequalities fostered by the change in farming technology" (BF, pg. 1526). In summary, the necessary conditions according to BF were (i) storeability and the existence of property rights, (ii) appropriable capital intensity that allowed unequal distribution of wealth to develop, and (iii) the formation of a state that ensured that unequal distribution of wealth could not be challenged. The fact that the data contains variation in more than only capital intensity will help in shedding light on this hypothesis, especially since BF effectively hint at a plausible interaction between capital intensity and other factors (most clearly, appropriability) in affecting inequality. For example, the coefficient estimate for $\beta_{\text{Capital}\times\text{App}}$ when the dependent variable is the income Gini is statistically significant and positive, just as BF suggest. However, this correlation appears to disappear when the dependent variable is the wealth Gini. Moreover, after adjusting for multiple hypothesis testing, the adjusted p-value increases above the 5% threshold which means it is plausible that the coefficient estimate matching BF's hypothesis could have also been by chance.

As I mentioned before, there is a literature in political economy (which includes MMP and BF) which finds that appropriability of resources does not only predict hierarchy and inequality, but also state capacity and the general enforcement of property rights. Moreover, this literature finds a positive correlation between all three factors (meaning, where there is more appropriability, there tends to be greater inequality, greater state capacity, and in turn, a greater enforcement of property rights). I calculate the pairwise correlation in Stoneworks Minecraft between measures of state capacity (total and per-capita tax payments as well as effective tax rates), intensity of nation-state presence (average share of commands in nation management), (lack of) property rights (average land claims and changes in ownership), and inequality at the group level in Table 4. I also estimate a similar regression specification to that of Table 3 in Table 6, but taking the state capacity and property rights variables as dependent variables instead of inequality, so as to see the relationship between appropriability and those dependent variables when controlling for other food attributes. Finally, I also regress inequality measures on the state capacity and property rights variables, taking the food attributes variables from Table 3 as controls in Table 5.

By and large, there is a significant and positive (pairwise) correlation between the state capacity variables (tax revenue and tax rate) and wealth inequality, though the highest correlation within the state capacity variables is between inequality and the number of players within a group. I also find a significant pairwise correlation between one of the property rights variables (daily changes in land ownership) and wealth inequality. After controlling for all previously mentioned variables simultaneously, the partial correlation between state capacity and income inequality persists while the partial correlation between state capacity and wealth inequality is statistically indistinguishable from zero. The largest estimated effect size for wealth inequality again corresponds to group size wherein a 1% increase in the number of players is associated with a 0.28 percentage point increase in the wealth Gini. I do not find a significant relationship between appropriability and state capacity variables (or between appropriability and the property rights variables). In other words, appropriability does not appear to predict significant differences in state capacity or property rights in Stoneworks Minecraft. This could be because there is no causal relationship between the variables in the first place, but it is worth mentioning that the effect sizes are relatively large (a one percentage point increase in appropriability is associated with a 2% average increase in tax revenue). Since my regression specification pools over all periods, it could be that the tests are sta-

Table 4: Pairwise Correlations Between State Capacity Variables and Inequality

	T.Rev.	G.S.	TRpC	T.Rate	N.M.	L.M.	-L.C.	-O.C.	I.G.	W.G.
Tax Revenue	1.000									
Group Size	0.009*	1.000								
Tax Rev. per Capita	0.993***	0.001	1.000							
Tax Rate	0.081***	0.063***	0.077***	1.000						
Nation Mgmt	-0.002	0.002	-0.002	0.018**	1.000					
Land Mgmt	0.001	−0.019***	0.002	0.085***	−0.041***	1.000				
(−1)× Land Claims	−0.010**	0.003	−0.015**	−0.158***	0.003	−0.088***	1.000			
(−1)× Ownership Change	−0.023***	0.010	−0.040***	−0.057***	−0.027**	−0.069***	0.080***	1.000		
Income Gini	0.014	0.202***	0.009	0.024*	-0.007	-0.012	0.009	0.005	1.000	
Wealth Gini	0.026**	0.717***	0.007	0.049***	−0.013*	−0.036***	0.004	−0.028**	0.095***	1.000

Notes: Table reports Pearson pairwise correlations between total daily tax payments (Tax Revenue), number of players within a group (Group Size), Tax Revenue / Group Size (Tax Revenue per Capita), share of daily total expenses in taxes (Tax Rate), number of commands related to nation management (Nation Mgmt), number of commands related to land management (including land claims) (Land Mgmt), within-group average of daily land claims (Land Claims), within-group average of daily changes to (existing) land ownership (Ownership Change), income Gini, and wealth Gini. All correlations are computed from daily group-level observations. Stars denote significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 5: State Capacity, Property Rights, and Food Sources

	IHS(T.Rev.) (1)	log(G.S.) (2)	IHS(TRpC) (3)	T.Rate (4)	N.M. (5)	L.M. (6)	-IHS(L.C.) (7)	-IHS(O.C.) (8)
β_{App}	2.167	0.353*	1.876	0.251	0.011	-0.048	0.014	0.235
	(2.625)	(0.174)	(2.385)	(0.190)	(0.014)	(0.086)	(0.234)	(0.208)
$\beta_{\text{Capital}\times\text{App}}$	2.900	0.205	2.726	0.105	-0.017	-0.129	0.474**	-0.153^{*}
	(1.910)	(0.346)	(1.781)	(0.121)	(0.013)	(0.068)	(0.153)	(0.069)
$\beta_{\text{App}\times\text{Renew}}$	-1.481	-0.017	-1.436	-0.229	-0.011	0.037	-0.009	-0.190
	(3.015)	(0.198)	(2.734)	(0.210)	(0.007)	(0.095)	(0.287)	(0.213)
$\beta_{\text{App}\times\text{Land}}$	-0.889	-0.262^{*}	-0.644	-0.012	0.003	0.037	-0.017	0.009
	(1.150)	(0.106)	(1.019)	(0.069)	(0.007)	(0.044)	(0.167)	(0.064)
Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,865	6,865	6,865	6,431	6,865	6,865	6,865	6,865
Cohorts	963	963	963	912	963	963	963	963
Minimum groups per period	37	37	37	37	37	37	37	37
Median groups per period	70	70	70	70	70	70	70	70
Maximum groups per period	143	143	143	143	143	143	143	143
R squared	0.154	0.235	0.154	0.127	0.159	0.168	0.182	0.164
Mean (raw) dep. var.	14,971	3.008	4,845	0.110	0.013	0.318	0.307	0.102

Notes: The table presents results from regressions of the total daily tax payments (T.Rev.), number of players within a group (G.S.), T.Rev. / G.S. (TRpC), share of daily total expenses in taxes (T.Rate), number of commands related to nation management (N.M.), number of commands related to land management (including land claims) (L.M.), within-group average of daily land claims (L.C.), and within-group average of daily changes to (existing) land ownership (O.C.) of spatially clustered groups in a day (by HDBSCAN) on the share of food gain from crafted foods (Capital), the share from appropriable foods (App), the share from renewable foods (Renew), the share from land-dependent foods (Land), and interactions of those food shares in the same day. Controls include the inverse hyperbolic sine (IHS) of total group income and the IHS of total food gain for both. Standard errors are robust to serial dependence (Driscoll and Kraay, 1998), Romano-Wolf p-value adjustment accounts for hypothesis testing in Table 3 and Table 5.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
(Romano-Wolf Adjusted: ^{r} $p^{RW} < 0.05$, ^{rr} $p^{RW} < 0.01$, ^{rrr} $p^{RW} < 0.001$).

Table 6: Inequality, State Capacity, and Property Rights (+ Food Sources Controls)

	Income Gini (1)	Income Gini (2)	Wealth Gini (3)	Wealth Gini (4)
$\beta_{\text{IHS(Tax Revenue)}}$	$0.003^{***,rrr}$	$0.003^{***,rrr}$	0.001	0.001
	(0.001)	(0.001)	(0.000)	(0.000)
$\beta_{\log\text{(Group Size)}}$	$0.046^{***,rrr}$	$0.045^{***,rrr}$	$0.276^{***,rrr}$	$0.277^{***,rrr}$
	(0.004)	(0.004)	(0.004)	(0.004)
$\beta_{\text{Tax Rate}}$	$-0.044^{***,rrr}$	$-0.044^{***,rrr}$	0.002	0.001
	(0.011)	(0.011)	(0.008)	(0.008)
$\beta_{\text{Nation Mgmt}}$	0.009	0.014	-0.042	-0.041
	(0.045)	(0.046)	(0.061)	(0.061)
$\beta_{\text{Land Mgmt}}$	$-0.024^{**,rr}$	$-0.023^{*,r}$	$-0.026^{**,rr}$	$-0.026^{**,rr}$
	(0.009)	(0.009)	(0.008)	(0.008)
$\beta_{-\text{IHS(Land Claims)}}$	0.002	0.002	0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.002)
$\beta_{-\text{IHS(Ownership Change)}}$	-0.003	-0.003	-0.010^{*}	-0.010^{*}
	(0.009)	(0.009)	(0.004)	(0.004)
Cohort FEs	Yes	Yes	Yes	Yes
Decomposed Food	No	No	No	No
Controls	Yes	Yes	Yes	Yes
Food Interactions	No	Yes	No	Yes
Observations	6,377	6,377	7,027	7,027
Cohorts	909	909	933	933
Minimum groups per period	38	38	38	38
Median groups per period	72	72	81	81
Maximum groups per period	137	137	146	146
R squared	0.207	0.208	0.655	0.655
Mean dep. var.	0.039	0.039	0.608	0.608

Notes: The table presents results from regressions of the income and wealth within-group Gini of spatially clustered groups in a day (by HDBSCAN) on the total daily tax payments (Tax Revenue), number of players within a group (Group Size), share of daily total expenses in taxes (Tax Rate), number of commands related to nation management (Nation Mgmt), number of commands related to land management (including land claims) (Land Mgmt), within-group average of daily land claims (Land Claims), and within-group average of daily changes to (existing) land ownership (Ownership Change), controlling for the share of food gain from crafted foods (Capital), the share from appropriable foods (App), the share from renewable foods (Renew), the share from land-dependent foods (Land), and interactions of those food shares in the same day. Additional controls include the inverse hyperbolic sine (IHS) of total group income and the IHS of total food gain for both. Standard errors are robust to serial dependence (Driscoll and Kraay, 1998), Romano-Wolf p-value adjustment accounts for hypothesis testing in Table 3 and Table 6.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
(Romano-Wolf Adjusted: $^{r}\ p^{RW} < 0.05$, $^{rr}\ p^{RW} < 0.01$, $^{rrr}\ p^{RW} < 0.001$).

tistically underpowered to observe substantial differences after playing for several months. Moreover (as I mentioned before), because these correlations are observed under the complete dataset as opposed to exploiting the exogenous variation from random assignment of starting locations, there is no guarantee that these coefficient estimates identify a causal relationship between the variables.

4.2 Main Effects on Income and Wealth Inequality

From this point on, I use random assignment of starting locations from players in I_R to study the causal effect of starting location features on wealth and income inequality. The results of estimating the baseline specification from Section 3.4 are reported in Table 7 for income and Table 8 for wealth.

There is no statistically significant effect on the income Gini coefficient from increasing the share of food production in capital-intensive foods, appropriable foods, renewable foods, or land-dependent foods. While the coefficient estimates change if I add interaction terms between the food attribute shares (see Table A6 in the Appendix), the standard errors are large enough that I cannot reject that there is zero effect from attributes on the income Gini coefficient. This is further supported by the fact that the coefficient estimates for the effect on income percentiles are also not significant.

Wealth inequality, on the other hand, does appear to be affected by food attribute shares, state capacity variables (measured by the tax rate), and existing levels of inequality. The effect sizes are small, with a shift towards fully capital-intensive appropriable land-dependent renewable food sources causing an estimated increase of 0.087 (s.e. $= 0.019$, p-value < 0.001) in the average within-group Gini coefficient for wealth and an estimated increase in average group size of 0.19% (s.e. $= 0.03\%$, p-value < 0.001).[20]

The effect sizes are much larger once I add interaction terms to the regression (see Table 9). Capital intensity, appropriability, renewability, and land-dependence shares all affect the distribution of wealth within a group. The estimates are strongly

[20] Unless otherwise stated, these are conventional p-values; Romano-Wolf adjusted p-values are always either pointed out explicitly as 'adjusted' or with the RW (or r) superscripts.

Table 7: Within-Group Income Ineq. and I_R Location Features

	Inc. Gini (1)	IHS(P10) (2)	IHS(P50) (3)	IHS(P90) (4)	IHS(G.Inc.) (5)	log(G.Size) (6)
γ_{Capital}	0.016	-0.552^{*}	-0.490^{*}	-0.477^{*}	-0.454^{*}	$0.043^{**,r}$
	(0.014)	(0.223)	(0.217)	(0.215)	(0.213)	(0.015)
γ_{App}	−0.026	0.019	−0.044	−0.081	−0.093	$0.078^{***,rrr}$
	(0.015)	(0.353)	(0.353)	(0.355)	(0.356)	(0.018)
γ_{Renew}	−0.002	−0.160	−0.167	−0.170	−0.175	0.019
	(0.007)	(0.241)	(0.243)	(0.245)	(0.245)	(0.013)
γ_{Land}	−0.004	0.223	0.212	0.204	0.203	$0.054^{***,rrr}$
	(0.008)	(0.165)	(0.161)	(0.160)	(0.160)	(0.010)
$\gamma_{\text{Tax Rate}}$	0.009	-2.719^{*}	-2.694^{*}	-2.663^{*}	-2.697^{*}	$-0.616^{***,rrr}$
	(0.050)	(1.079)	(1.095)	(1.105)	(1.110)	(0.039)
$\gamma_{\text{Income Gini}}$	0.075	−4.699	−4.430	−4.326	−4.414	−0.056
	(0.132)	(3.258)	(3.357)	(3.404)	(3.434)	(0.089)
$\gamma_{\text{Wealth Gini}}$	−0.020	0.747	0.722	0.672	0.631	$-0.293^{***,rrr}$
	(0.026)	(0.627)	(0.645)	(0.652)	(0.652)	(0.020)
Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Decomposed Food	No	No	No	No	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Interactions	No	No	No	No	No	No
Observations	2,197	2,218	2,218	2,218	2,218	14,556
Cohorts	361	362	362	362	362	1,110
Min. groups/per.	102	102	102	102	102	102
Med. groups/per.	159	159	159	159	159	159
Max. groups/per.	272	272	272	272	272	272
R squared	0.164	0.233	0.234	0.234	0.234	0.265
Mean (raw) dep. var.	0.039	65,960	69,916	74,814	78,015	3.008

Notes: The table presents results from regressions of the within-group outcomes of spatially clustered groups in a day (by HDBSCAN) on aggregate starting location features for randomly assigned members of the group. The outcomes include the within-group income Gini coefficient (Inc. Gini), the within-group income percentiles (P10, P50, P90), the sum of all income within the group (G. Inc.), and the number of players within a group (G.Size). The features include the average share of food gain from crafted foods (Capital), appropriable foods (App), renewable foods (Renew), and land-dependent foods (Land) of the players surrounding the starting locations of randomly assigned group members; the average share of expenses in tax payments (Tax Rate) of players surrounding the starting locations of randomly assigned group members; the average within-group Gini coefficient in income (Income Gini) and wealth (Wealth Gini) of players surrounding the starting locations of randomly assigned group members. Controls include other starting location features (see section C), including variables related to resource type distributions, population density, food surplus, share of income in tax collection, market penetration, land/nation management, land claims, town invitations, town creation, arrows shot, share of items collected in food, share of randomly assigned players, average tenure and playtime, transfer payments, and existing income/wealth levels. Standard errors are robust to serial dependence (Driscoll and Kraay, 1998), Romano-Wolf p-value adjustment accounts for hypothesis testing in Table A6, 8, and 9.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
(Romano-Wolf Adjusted: ^{r} $p^{RW} < 0.05$, ^{rr} $p^{RW} < 0.01$, ^{rrr} $p^{RW} < 0.001$).

Table 8: Within-Group Wealth Ineq. and I_R Location Features

	W. Gini	IHS(P10)	IHS(P50)	IHS(P90)	IHS(G.Wealth)	log(G.Size)
	(1)	(2)	(3)	(4)	(5)	(6)
γ_{Capital}	$0.038^{***,rrr}$	$-0.679^{***,rr}$	$-0.707^{***,r}$	-0.176	-0.163	$0.043^{**,r}$
	(0.008)	(0.180)	(0.192)	(0.154)	(0.158)	(0.015)
γ_{App}	$0.039^{**,rr}$	$-0.851^{***,rr}$	-0.753^{**}	-0.130	-0.101	$0.078^{***,rrr}$
	(0.013)	(0.200)	(0.247)	(0.304)	(0.314)	(0.018)
γ_{Renew}	-0.006	0.170	0.189	0.483^{*}	0.500^{**}	0.019
	(0.008)	(0.165)	(0.186)	(0.184)	(0.188)	(0.013)
γ_{Land}	$0.016^{**,rr}$	-0.158	-0.078	0.094	0.112	$0.054^{***,rrr}$
	(0.005)	(0.130)	(0.156)	(0.168)	(0.172)	(0.010)
$\gamma_{\text{Tax Rate}}$	$-0.209^{***,rrr}$	0.599	-0.184	$-4.885^{***,rrr}$	$-5.208^{***,rrr}$	$-0.616^{***,rrr}$
	(0.025)	(0.593)	(0.733)	(0.796)	(0.809)	(0.039)
$\gamma_{\text{Income Gini}}$	-0.055	0.673	1.048	0.080	0.133	-0.056
	(0.062)	(1.547)	(1.788)	(1.807)	(1.832)	(0.089)
$\gamma_{\text{Wealth Gini}}$	$-0.090^{***,rrr}$	0.735^{*}	0.152	$-1.712^{***,rrr}$	$-1.859^{***,rrr}$	$-0.293^{***,rrr}$
	(0.017)	(0.313)	(0.346)	(0.373)	(0.380)	(0.020)
Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Decomposed Food	No	No	No	No	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Interactions	No	No	No	No	No	No
Observations	8,150	14,556	14,556	14,556	14,556	14,556
Cohorts	668	1,110	1,110	1,110	1,110	1,110
Min. groups/per.	102	102	102	102	102	102
Med. groups/per.	159	159	159	159	159	159
Max. groups/per.	272	272	272	272	272	272
R squared	0.226	0.171	0.178	0.234	0.236	0.265
Mean (raw) dep. var.	0.608	6,708	28,693	124,771	171,852	3.008

Notes: The table presents results from regressions of the within-group outcomes of spatially clustered groups in a day (by HDBSCAN) on aggregate starting location features for randomly assigned members of the group. The outcomes include the within-group wealth Gini coefficient (W. Gini), the within-group wealth percentiles (P10, P50, P90), the sum of all wealth within the group (G. Wealth), and the number of players within a group (G.Size). The features include the average share of food gain from crafted foods (Capital), appropriable foods (App), renewable foods (Renew), and land-dependent foods (Land) of the players surrounding the starting locations of randomly assigned group members; the average share of expenses in tax payments (Tax Rate) of players surrounding the starting locations of randomly assigned group members; the average within-group Gini coefficient in income (Income Gini) and wealth (Wealth Gini) of players surrounding the starting locations of randomly assigned group members. Controls include other starting location features (see section C), including variables related to resource type distributions, population density, food surplus, share of income in tax collection, market penetration, land/nation management, land claims, town invitations, town creation, arrows shot, share of items collected in food, share of randomly assigned players, average tenure and playtime, transfer payments, and existing income/wealth levels. Standard errors are robust to serial dependence (Driscoll and Kraay, 1998), Romano-Wolf p-value adjustment accounts for hypothesis testing in Table 7, A6, and 9.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
(Romano-Wolf Adjusted: ^{r} $p^{RW} < 0.05$, ^{rr} $p^{RW} < 0.01$, ^{rrr} $p^{RW} < 0.001$).

suggestive of non-separable effects, with many of the interaction coefficients being often large (relative to the non-interaction terms) and statistically significant. For instance, consider a group wherein the randomly assigned starting locations were exposed to highly capital intensive and appropriable food production, on average. Relying only on $(\hat{\gamma}_{\text{Capital}}, \hat{\gamma}_{\text{App}}, \hat{\gamma}_{\text{Capital}\times\text{App}})$, the coefficient estimates would not appear to imply a significant increase in average within-group wealth inequality ($\hat{\gamma}_{\text{Capital}} + \hat{\gamma}_{\text{App}} + \hat{\gamma}_{\text{Capital}\times\text{App}} = 0.133$, s.e. $= 0.126$, p-value ≈ 0.291). However, the food sources that exhibit capital intensity and appropriability at the same time are also all renewable food sources. When one considers renewability as a necessary condition for capital intensive and appropriable food production, one gets an unambigous increase in wealth inequality ($\hat{\gamma}_{\text{Capital}} + \hat{\gamma}_{\text{App}} + \hat{\gamma}_{\text{Capital}\times\text{App}} + \hat{\gamma}_{\text{Renew}} + \hat{\gamma}_{\text{Capital}\times\text{Renew}} + \hat{\gamma}_{\text{App}\times\text{Renew}} = 0.353$, s.e. $= 0.105$, p-value < 0.001). As it so happens, there are only two food sources in Minecraft that exhibit these three properties at the same time: cake (which is land dependent) and honey bottle (which is not land dependent). Considering a group exposed to a starting location where only cake is produced (by summing all the food attribute coefficients) implies an estimated increase of 0.219 (s.e. $= 0.114$, p-value ≈ 0.055) on the average wealth Gini coefficient. In general, greater land-dependent production in a starting location tends to depress wealth inequality from emerging; all the coefficient estimates for land-dependence interactions are negative, with some being statistically significant at the 0.1% level. These results do not change if I add higher-order interaction terms to consider all possible combinations of the food attributes.[21] In section 4.3, I elaborate further on the role of idiosyncratic food sources on my results.

In any case, this increase in wealth inequality from capital intensity and appropriability is primarily driven by disproportionate increases in the upper percentiles of wealth at the cost of decreases in the lower percentiles within a group: the average

[21] Author's note: I am in the process of producing a figure that summarizes this information from the 16 coefficients in an elegant way; for now, I report here the basic results of doing the same exercise with the higher-order interactions model. Considering capital intensity and appropriability alone gives you an estimated effect of -2.423 (s.e. $= 2.743$, p-value ≈ 0.377) whereas accounting for the fact that both at the same time imply renewability gives you an estimated effect of 1.001 (s.e. $= 0.468$, p-value ≈ 0.032). In my dataset, the effect sizes become even larger when all the interaction terms are considered; this comes at the cost of making the economics harder to explain as well as having comparably underpowered coefficient estimates. In fact, the coefficient estimates are all statistically indistinguishable from zero even if the combined food attributes in the model is able to deliver statistically significant results.

Table 9: Within-Group Wealth Ineq. and I_R Location Features(+Interactions)

	W. Gini (1)	IHS(P10) (2)	IHS(P50) (3)	IHS(P90) (4)	IHS(G.Wealth) (5)	log(G.Size) (6)
γ_{Capital}	-0.127^{*}	1.976	1.731	-0.248	-0.369	-0.282^{**}
	(0.064)	(1.318)	(1.632)	(1.704)	(1.760)	(0.087)
γ_{App}	0.113	-2.197	-1.649	0.287	0.398	0.255^{*}
	(0.061)	(1.463)	(1.782)	(1.438)	(1.476)	(0.098)
γ_{Renew}	0.014	0.074	0.130	0.767^{**}	0.815^{**}	$0.083^{***,rr}$
	(0.011)	(0.259)	(0.340)	(0.290)	(0.297)	(0.021)
γ_{Land}	$0.270^{***,rrr}$	$-6.071^{***,rrr}$	$-6.287^{***,rrr}$	$-4.649^{***,rrr}$	$-4.600^{***,rrr}$	$0.476^{***,rrr}$
	(0.031)	(0.849)	(0.957)	(1.071)	(1.101)	(0.053)
$\gamma_{\text{Capital}\times\text{App}}$	0.147	-1.828	0.517	$7.586^{**,r}$	$8.296^{**,rr}$	$0.938^{***,rrr}$
	(0.116)	(2.239)	(2.796)	(2.804)	(2.866)	(0.193)
$\gamma_{\text{Capital}\times\text{Renew}}$	$0.257^{**,rr}$	-4.151^{**}	-3.897^{*}	-1.102	-0.984	$0.437^{***,rr}$
	(0.085)	(1.307)	(1.590)	(1.589)	(1.645)	(0.114)
$\gamma_{\text{Capital}\times\text{Land}}$	-0.109^{**}	1.818^{*}	1.648	1.033	1.019	-0.168^{**}
	(0.038)	(0.782)	(0.934)	(1.086)	(1.113)	(0.057)
$\gamma_{\text{App}\times\text{Renew}}$	-0.050	-0.582	-0.984	-2.678	-2.838	-0.244^{*}
	(0.059)	(1.450)	(1.903)	(1.427)	(1.469)	(0.101)
$\gamma_{\text{App}\times\text{Land}}$	-0.046	$2.853^{***,rrr}$	$2.672^{***,rr}$	$2.795^{***,rr}$	$2.867^{***,rr}$	0.034
	(0.030)	(0.710)	(0.678)	(0.626)	(0.634)	(0.042)
$\gamma_{\text{Renew}\times\text{Land}}$	$-0.248^{***,rrr}$	$5.412^{***,rrr}$	$5.754^{***,rrr}$	$4.239^{***,rrr}$	$4.193^{***,rr}$	$-0.433^{***,rrr}$
	(0.031)	(0.801)	(0.920)	(1.075)	(1.103)	(0.055)
$\gamma_{\text{Tax Rate}}$	$-0.224^{***,rrr}$	0.807	0.022	$-4.789^{***,rrr}$	$-5.121^{***,rrr}$	$-0.642^{***,rrr}$
	(0.026)	(0.612)	(0.752)	(0.803)	(0.815)	(0.041)
$\gamma_{\text{Income Gini}}$	-0.041	0.554	0.969	0.284	0.365	-0.002
	(0.063)	(1.531)	(1.769)	(1.803)	(1.827)	(0.093)
$\gamma_{\text{Wealth Gini}}$	$-0.087^{***,rrr}$	0.778^{*}	0.212	$-1.639^{***,rrr}$	$-1.784^{***,rrr}$	$-0.292^{***,rrr}$
	(0.017)	(0.315)	(0.351)	(0.374)	(0.381)	(0.020)
Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Decomposed Food	No	No	No	No	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,150	14,556	14,556	14,556	14,556	14,556
Cohorts	668	1,110	1,110	1,110	1,110	1,110
Min. groups/per.	102	102	102	102	102	102
Med. groups/per.	159	159	159	159	159	159
Max. groups/per.	272	272	272	272	272	272
R squared	0.232	0.175	0.181	0.236	0.238	0.271
Mean (raw) dep. var.	0.608	6,708	28,693	124,771	171,852	3.00

Notes: The table presents results from regressions of the within-group outcomes of spatially clustered groups in a day (by HDBSCAN) on aggregate starting location features for randomly assigned members of the group. The outcomes include the within-group wealth Gini coefficient (W. Gini), the within-group wealth percentiles (P10, P50, P90), the sum of all wealth within the group (G. Wealth), and the number of players within a group (G.Size). The features include the average share of food gain from crafted foods (Capital), appropriable foods (App), renewable foods (Renew), and land-dependent foods (Land) of the players surrounding the starting locations of randomly assigned group members; the average share of expenses in tax payments (Tax Rate) of players surrounding the starting locations of randomly assigned group members; the average within-group Gini coefficient in income (Income Gini) and wealth (Wealth Gini) of players surrounding the starting locations of randomly assigned group members. Controls include other starting location features (see section C), including variables related to resource type distributions, population density, food surplus, share of income in tax collection, market penetration, land/nation management, land claims, town invitations, town creation, arrows shot, share of items collected in food, share of randomly assigned players, average tenure and playtime, transfer payments, and existing income/wealth levels. Standard errors are robust to serial dependence (Driscoll and Kraay, 1998), Romano-Wolf p-value adjustment accounts for hypothesis testing in Table 7, 8, and A6. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. (Romano-Wolf Adjusted: ^{r} $p^{RW} < 0.05$, ^{rr} $p^{RW} < 0.01$, ^{rrr} $p^{RW} < 0.001$).

10th percentile of wealth decreases by 6.708% (s.e. 2.304, p-value $\approx$ 0.004), the average median wealth decreases by 4.152% (s.e. 2.825, p-value $\approx$ 0.142), and the average 90th percentile increases by 4.612% (s.e. 2.903, p-value $\approx$ 0.112). While the standard errors are too large to reject that the changes in each decile of the wealth distribution are non-zero, it is the case that the estimated change in the average percentile from capital-intensive appropriable food production is increasing in the percentile level. To see this more clearly, I estimate the same regression specification using all within-group wealth deciles as dependent variables in Figure 11. Whereas the coefficient estimates for $(\hat{\gamma}_{\text{Capital}}, \hat{\gamma}_{\text{App}}, \hat{\gamma}_{\text{Renew}}, \hat{\gamma}_{\text{Capital}\times\text{Renew}}, \hat{\gamma}_{\text{App}\times\text{Renew}})$ do not significantly change across percentiles and imply relatively modest effect sizes, $\hat{\gamma}_{\text{Capital}\times\text{App}}$ decreases first in the lower percentiles and then, from the third decile onward, gradually increases in the upper percentiles with each coefficient estimate being greater than the last. The estimated effect on the top earner within a group from exposure to capital intensive and appropriable food production is an increase of 5.118% in wealth (s.e. = 2.926, p-value $\approx$ 0.080).

Independently of whether I estimate the regression specification with and without interactions between the food attributes, inequality unambigously decreases when groups are exposed to higher average tax rates and greater wealth inequality in their starting locations. A 1 percentage point (pp) increase in the average tax rate surrounding a group's average starting location causes a 0.2pp decrease in the wealth Gini; a 1pp increase in the average wealth Gini surrounding a group's average starting location causes a 0.08pp decrease instead. As the bottom right of Figure 11 clearly demonstrates, this effect is driven by moderate decreases in the upper percentiles of the distribution and small increases in the bottom percentiles of the distribution. This also has a significant effect on wealth accumulation, with a 1pp increase in the average tax rate surrounding a group's average starting location causing a 0.05% decrease in total group wealth. Since the tax rate is measured as the share of daily expenses in tax payments and observations are at the group-daily level, this can also be interpreted as follows: if a group's starting locations were surrounded by players whose only expense was paying taxes the day before, this causes a 5% decrease in the average wealth level of the group. Since the increase in the bottom percentiles is smaller in scale than the decrease in the top percentiles,

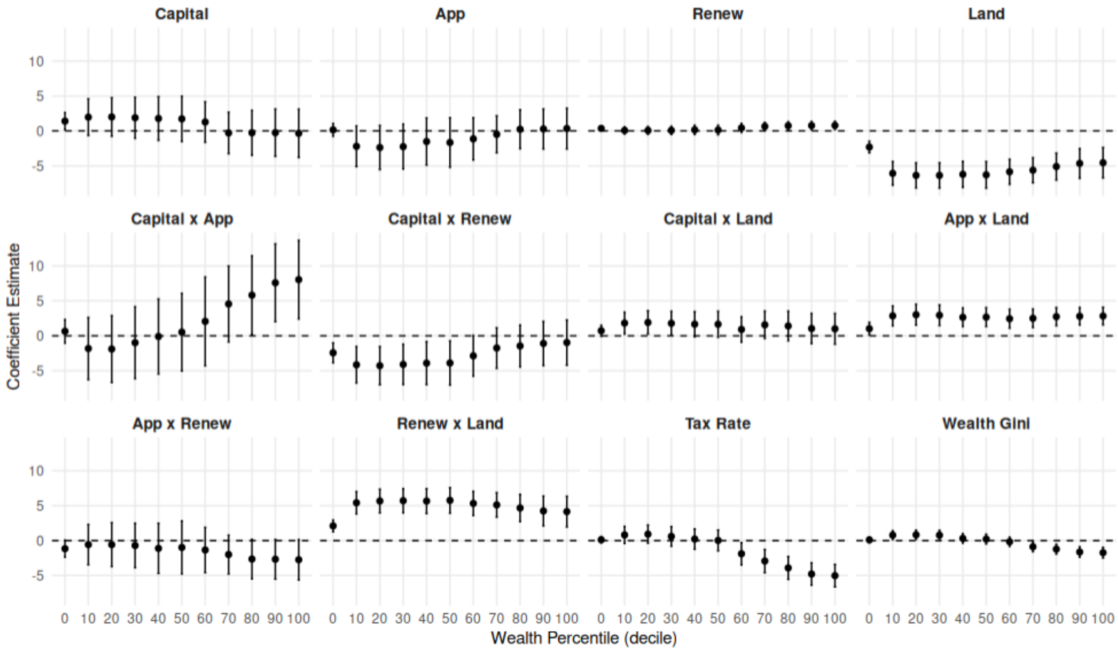

Figure 11: Coefficient estimates from regressing within-group wealth deciles on I_R location features with interactions (Table 9).

this is suggestive evidence that this effect might be driven by high productivity players being more likely to leave the group after events of heavy taxation. There is a similar dynamic with a smaller effect size with how existing wealth inequality in a starting location later affects wealth inequality in the group. In both cases, the reduction in average group wealth coincides with a reduction in the average group size.

4.3 Decomposition by Food Sources

While the estimated model from Section 4.2 suggests that capital intensity, appropriability, renewability, and land dependence are significant drivers of wealth inequality, it is worth stating that part of the variation may also be explained by the specific food sources that dominate each food attribute combination. For instance, there could be idiosyncratic properties of the food sources in each food attribute combination which may affect the distribution of wealth whilst coincidentally matching the properties that BF and MMP purported to be important for the emergence of inequality. In this section, I re-estimate the regression specification with each food attribute combination separately as opposed to using interaction terms and further analyze properties of each food attribute combination in how it could have led to changes in the distribution of wealth.

Modifying the feature set. In the original feature set of Section 3.4, I included the lagged average shares of food gain in capital intensive, appropriable, renewable, and land dependent foods of players surrounding a randomly assigned starting location. Because of the fact that these food attributes are correlated by how the foods were designed by Minecraft, I relied on the fact that these shares are not perfectly correlated for being able to identify the effect of these food attributes separately. To uncover more specifically what is driving the effect, I swap the 4 average shares of food attribute features for the following:

- **Lagged average share of food pickups, food crafted, food used as input, food dropped, food purchased, and food sold in all category combinations of capital-intensive, appropriable, renewable, and land dependent foods of players surrounding a randomly assigned starting location.** By considering all (non-empty) food attribute combinations, we get 54 different location features total.
- **Lagged average share of food gain (food use) (in nutritional value) by acquisition methods (whether the food was acquired through pickups, purchases, or crafting and whether the food was used as a drop, sold, or as an input for crafting) of players surrounding a randomly assigned starting location.** These 6 location features allow me to control for how food is acquired or utilized by players to disentangle the acquisition method and use of food from the actual attributes of the food, especially since capital intensity is defined by whether crafting is part of the food production process.

At this point, it is worth reminding that this sudden increase of 58 in the number of location features is, again, mitigated by the Romano-Wolf p-value adjustment for multiple hypothesis testing, which in principle should decrease statistical power for finding any effect on wealth inequality, not to mention in such a narrow subset of covariates.

The complete set of (non-empty) food attribute combinations is represented by the following tuples in $\{0,1\}^4$ with each element being equal to one when it satisfies an attribute and zero when not: $(0,0,0,0)$ (non-appropriable non-capital intensive non-renewable non-land dependent foods; contains raw fish and chorus fruit), $(0,1,0,0)$ (non-appropriable, capital-intensive, non-renewable, non-land dependent foods; contains cooked fish, dried kelp, golden apple, pufferfish, and suspicious stew), $(0,1,0,1)$ (non-appropriable capital-intensive non-renewable land-dependent foods; contains golden carrots), $(0,1,1,0)$ (non-appropriable capital-intensive renewable non-land dependent foods; contains cooked meats), $(0,1,1,1)$ (non-appropriable capital-intensive renewable land-dependent foods; contains baked potato, beetroot soup, bread, cookie, and pumpkin pie), $(1,0,1,0)$ (appropriable non-capital intensive renewable non-land dependent foods; contains apple, glow berries, raw meat, rotten flesh, sweet berries, and spider eye), $(1,0,1,1)$ (appropriable non-capital intensive renewable land-dependent foods; contains beetroot, carrot, melon slice, potato), $(1,1,1,0)$ (appropriable capital-intensive renewable non-land dependent foods; contains honey bottle), and $(1,1,1,1)$ (appropriable capital intensive renewable land-dependent foods; contains cake).

The results of the regression are summarized in Table A7 and A8 in the Appendix.[22] Most of the food categories have either no statistically significant effect on the wealth distribution or relatively small effect sizes. The food categories which do have an effect, however, have an outsized effect on the wealth and income distribution compared to other factors, including tax rates and wealth inequality in starting locations.

Income inequality increases most sharply in locations where nearby players rely on capital intensive appropriable and renewable foods (i.e., honey bottles). An increase in local share of only honey bottles in a starting location of 1pp causes an increase in the within-group income Gini of 0.56pp (s.e. = 0.26 pp), holding all other features fixed. The inequality in daily income within groups is low (about 0.02 on average, s.d. = 0.12), which makes this effect size many times greater than the mean of the dependent variable. This increase in inequality is again driven by disproportionate increases in the upper percentiles of income relative to the lower percentiles within

[22] Author's note: currently in the process of finding a good way to summarize these tables, probably a figure similar to Figure A14 and A15 in the Appendix.

the group. At the individual level, increased exposure to honey bottle production of 1pp causes an increase in the likelihood of belonging to the top percentile of 0.87pp (s.e. = 0.12pp); likewise, an individual player's share of the total income of his group also increases by 0.54 pp (s.e. = 0.18pp). This effect on the income distribution is however not sufficient to generate significant differences in the wealth distribution, which must mean that honey bottles are not the sole driver of the wealth inequality caused by capital-intensive and appropriable food production.

Wealth inequality is dampened most sharply by the use of capital-intensive non-appropriable land-dependent renewable foods as craft inputs (i.e., the use of baked potato as an input). Baked potato is only a crafting input for one food source in Minecraft, the rabbit stew. The effect size is even higher than that of honey bottles: a 1pp increase in the average share of baked potato inputs causes a decrease in the average wealth Gini of about 1.93pp (s.e. = 0.45pp). This effect is largely driven by an aggressive flattening of the wealth distribution within groups: whereas the 10th percentile has a large but non-significant gain of about 15% on average (s.e. 8%), the 90th percentile decreases by (non-significant) average of 16% (s.e. 10%). The same increase of 1pp also causes a reduction in the average ratio between the top and bottom earners of about 36% (s.e. = 18.53%); the ratio between the median and the bottom decreases by 46% (s.e. = 19%).

One natural question for the reader might be if there is anything special about honey bottles and rabbit stew as food sources in Minecraft. As it turns out, they are food sources with not just some of the highest nutritional values, but also with other extreme properties relative to other foods

Because of technical limitations with the game having many bee hives at once, the supply of bee hives for honey production is highly regulated by Stoneworks Minecraft and can only be purchased in AdminShops. Of all the food sources in Minecraft, it has the highest market price for setting up with a high fixed cost of 10,000S$ for a single bee hive; for reference, the 75th wealth percentile in Stoneworks is 190S$. At the same time, it involves negligible marginal labor to produce honey bottles once a bee hive is installed: all the player needs to do is right click the bee hive to collect honey to acquire a stable supply of food. This high barrier to entry makes it especially inaccessible to less wealthy players, thus causing a greater gap in income inequality as only wealthy players are able to produce and sell this food source for a stable income.

Rabbit stew requires the greatest number of crafting inputs compared to all other food sources in Minecraft. Moreover, some of these inputs, such as mushrooms, are impossible to farm in Stoneworks Minecraft and thus require foraging to produce. The diversity in the production inputs (combining rabbit, baked potato, wooden bowls, and mushrooms) makes producing and relying on a diet of rabbit stew particularly labor intensive. This complexity in production may contribute independently from capital intensity and appropriability to its inequality reducing effect, since requiring multiple inputs may limit the ability of elite players to appropriate the means of production not just at the final good stage, but also at the intermediate stages compared with foods produced through simpler processes. If the inputs are scarce and spatially dispersed, this could make the income generating process "dispersing" (Germano 2022), which may lead to low inequality being a feature of maximizing within-group income growth. These cases suggest that while the food attributes capture broad technological differences that are predictive of inequality, these results could also be driven by idiosyncratic characteristics of specific foods.

5 Discussion

The results of this paper highlight the importance of food production and its attributes in shaping inequality and economic development. My choice to center this analysis on food sources and to decompose them according to the few attributes I selected is directly informed by what the literature in the broader social sciences and humanities (including economics) has found to be important determinants in the rise of inequality.

5.1 Appropriability

My findings are consistent with a recent strand of literature in political economy that argues for appropriability of resources being a strong predictor for state capacity, the rise of hierarchy, and the general enforcement of property rights (Mayshar, Moav, and Neeman, 2017; Mayshar, Moav, and Pascali, 2022; Huning and Wahl, 2023). The core of Mayshar, Moav, and Neeman's (2017) theoretical results is that technological changes that improve the ability to observe farming output should induce greater state capacity, increased inequality, and weaker property rights. This is, the theory claims, because of the increased reliability with which the elite can extract the economic surplus of farming. This theory bundles together a rationalization for the positive correlation seen empirically between state capacity, inequality, autocracy, and appropriability in premodern farming states. Mayshar and his coauthors convincingly showcase this relationship by making qualitative comparisons between Ancient Egypt and Northern Mesopotamia based on historical accounts. Mayshar, Moav and Pascali (2022) show that the relative productivity of more appropriable crops (cereal grains compared to tubers) is positively correlated with the level of hierarchy in a society throughout different episodes in history, even after controlling for land productivity and other relevant factors. Huning and Wahl use spatial caloric suitability data from Galor and Özak (2014, 2015) to show a strong positive correlation between the observability of caloric suitability (measured by between-neighbor spatial variation) and several variables indicative of state capacity in the Holy Roman Empire, including the number of administrative buildings, Imperial war tax revenues, and wealth tax revenues. Whereas I find that appropriability has a role to play in generating income and wealth inequality in my data, I do not find significant effects from appropriability in food production on the level of tax payments, sudden changes in land ownership, or the number of land claims. This suggests that, at least in this setting, appropriation could generate inequality without immediately translating into stronger state capacity or significant differences in property rights.

That being said, reconciling the apparent causal link between appropriability and inequality with the lack thereof with state capacity and property rights could be merely a matter of timing. The processes I observe in the data happen in a matter of only three months whereas the processes this literature studies could have happened in a matter of millennia - indeed, one possibility could be that repeated exposure to appropriable food sources could have caused increased exposure to economic inequality but the emergence of massive state capacity could have happened only after "people lost the ability to imagine and enact other forms of social existence." Graeber and

Wengrow (2021) propose this hypothesis in their book, *The Dawn of Everything*, arguing that even if technological and ecological changes created the conditions for economic surplus that could feasibly be appropriated, long lasting levels of wealth inequality and state hierarchy still only arose thousands of years after the invention of agriculture. The long-term acceptance of structural inequality would have been a dramatic shift from the "aggressive egalitarianism" present in cultures prior (Bowles and Fochesato 2024), not to mention at odds with the apparently innate proclivity humans and even great apes seem to have for enacting fairness, at least in the lab (Proctor et al., 2013; Fehr and Charness, 2025). My findings in Stoneworks are at least consistent with a norm of aggressive egalitarianism: preexisting wealth inequality in a starting location does cause a small but significiant partail decrease in subsequent welath inequality.

5.2 Capital Intensity

Bowles and Fochesato (2024) (BF) argue that the cause of this cultural shift away from egalitarianism could have been the introduction of "farming technologies [that] raised the value of material wealth relative to labor." BF's main supporting evidence comes in an extensive review of the archaeological and anthropological literature on premodern societies as well as data on contemporary small-scale societies that show a positive correlation between ethnographers' estimates of capital intensity and the level of wealth inequality. The results from my analysis suggest that capital intensity plays an important role in shaping both inequality and economic development outright - the largest effects on economic outcomes from food composition, whether inequality enhancing or reducing, are all associated with the composition of capital intensive production of food as opposed to food production from hunting, foraging, or merely harvesting crops. At first glance, my results might seem to be at odds with BF's main hypothesis but they explicitly argue that capital intensity is only one of several necessary conditions for the emergence of enduring wealth inequality. As I mentioned before in section 4.1, the necessary conditions according to BF were (i) storeability and the existence of property rights, (ii) appropriable capital intensity that allowed unequal distribution of wealth to develop, and (iii) the formation of a state that ensured that unequal distribution of wealth could not be challenged.

The findings from my data are consistent with (i) and (ii) especially, by providing causal evidence that the interaction between capital intensity and appropriability is important for effectively inducing wealth inequality.

5.3 Other Theories of Inequality

The decomposition of food sources into being renewable and land-dependent was made primarily to be able to address the most classical theories (Morgan, 1877; Engels, 1884) for the origins of inequality, which is simply that the emergence of economic surplus made possible by agriculture could have intrinsically generated high levels of inequality. There are many challenges to this theory, many of which are well argued already by Bowles and Fochesato (see BF pg. 1488-1491). Insofar as land productivity can be taken as a predictor for economic surplus, there is also recent evidence that challenges this theory on the grounds of empirical data alone, in particular, the work on appropriability shown by Mayshar, Moav, and Pascali (2022) (MMP). One of the main results of MMP is that, once one controls for potential confounders including the relative land suitability of (the more appropriable) cereal grains over (the less appropriable) tubers, the statistical relationship between land productivity and state hierarchy disappears. Nonetheless, there remained the possibility for this hypothesis to potentially pan out as a significant explanatory variable given that it is indeed possible to disentangle the possibility of long-term food surplus (renewability) and whether a food source relies on farming (land dependence) from the appropriability and capital intensity because of the wide diversity of food sources in Minecraft that vary in those attributes. At best, my findings are at odds with the classical theory in terms of how farming should affect inequality: land dependence seems, if anything, to depress income and wealth inequality from emerging out of capital-intensive appropriable and renewable food sources. As for renewability, it does seem that the ability to produce a surplus is a necessary condition for inequality given that my findings on generating economic inequality rely on renewable food sources, but it is certainly no sufficient: I do not find significant differences in income or wealth inequality from shifting other food sources in production from non-renewables to renewables.

5.4 Virtual Worlds and External Validity

To the best of my knowledge, I am the first person to use data from Minecraft for economic research in an academic paper. Nonetheless, there is a small literature on generally using video games and "virtual worlds" in economics that this paper builds upon.

A virtual world, as Richard Bartle (2004) explains in his book *Designing Virtual Worlds*, is a self-contained computer simulated environment with five main characteristics: underlying automated rules (or *physics*) that enable players to make changes to the environment, unique and identifiable representations (or *avatars*) of individual players within the environment, interactions with immediate feedback (or in *real-time*), an identical environment for all players present at the same time (meaning, the virtual world is a *shared space*), and to some degree, *persistence*, meaning that the virtual world continues to exist and develop internally even when there are no players interacting with it.

One of the main benefits of using virtual worlds for research is that, as a byproduct of the technical requirements for meeting these five characteristics, an enormous amount of information must be transmitted and stored even for the simplest interactions between players. To illustrate this point, consider the information necessary for a meeting and exchange of items between two players in a virtual world. The would-be game designer or experimenter needs to receive information in real-time as to where the players are situated and send the players a visual representation of their locations that allow the players' avatars to interact with one another in the environment. The designer would need to keep track of the players' inventories once they begin to make their trade as well as provide an interface for the players to complete the exchange and, because of the persistence element, they would need to record a change in the ownership of the exchanged goods and have that information relayed in the user interface. By virtue of designing a virtual world, the game designer has to build an entire infrastructure of data management that make virtual world video games effectively double as massive data banks for human behavior. In densely populated virtual worlds such as *Black Desert Online* or *World of Warcraft*, the production of data scales up massively once these games allow many different complex systems to interact together with their large number of users.

The promise of virtual worlds in providing new and rich datasets for answering important questions in the sciences is part of what made them attractive for research throughout the 2000s and early 2010s. The beginnings of this research in economics starts with Edward Castronova's work on the fantasy-themed massively multiplayer online role-playing games, *Everquest* and *Everquest 2* (Castronova 2001). Castronova et al. (2009) are able to test the empirical validity of macroeconomic aggregation by using real-time data from *Everquest 2*. Their dataset included all 314 million transactions of the 1.6 million players of the game starting from January to September of 2006, complete with player interactions in teaming, trading, chat, achievements, demographics, and online orders. By measuring popular macroeconomic indicators like GDP and inflation, they show that the aggregate behavior of players in the game is consistent with the dynamics implied by the quantity theory of money. One of the strengths of virtual world data is that it constitutes a complete census of human behavior within its environment, which is especially useful for studying phenomena in general equilibrium or at a macroeconomic scale. Likewise, virtual world data can even be useful in testing statistical and econometric methods when there may not exist sufficiently large real world data available to the research and simulations could prove to be unrepresentative of the populations of study. Garnett et al. (2014) study "nearly 300 million user movements in the *EVE Online* universe from over 700 thousand user accounts over a period of three months" in order to test prediction methods for detecting unexpected gatherings in space. Finding a real-time dataset for 3D geo-positional data is much harder in the real world compared to acquiring the data from a virtual world, especially when one considers the ethics and privacy challenges of sharing and using real world location data. One of the main differences between this paper and others that have taken advantage of large datasets from virtual worlds is not only that I study a different virtual world (Stoneworks in Minecraft), but also that the natural experiment I study can be easily replicated thanks to the largely decentralized and user-generated properties of Minecraft. With the exception of populating the game with the players, all other technical aspects of the experiment involve readily available software that does not require the extensive partnerships experiments have to make with private industry that have become the norm with field experiments in economics (Levitt and List, 2009). The hope is that this work paves the way for the production of future experimental research in economic development that would otherwise only be possible through very costly interventions in foreign countries, many of which are impossible for researchers from less endowed institutions to replicate in practice.

One natural objection I anticipate against using Minecraft (or virtual worlds more generally) is whether any of the results I find from these experiments have external validity. After all, even though the players in the game are real people making real trades of virtual goods and services, Minecraft is ultimately just a video game. While, to my knowledge, there is not a literature in economics that provides evidence for individual behavior in virtual worlds being predictive of economic behavior in the real world, there *is* a literature in experimental economics that compares behavior in virtual worlds to behavior in the lab.[23] Chesney, Chuah, and Hoffman (2009) find no significant systematic differences in how players from *Second Life* play the Ultimatum Game (Roth et al., 1991; Hoffman et al., 1994; Chuah et al., 2007), the Dictator Game (Forsythe et al., 1994; Carpenter, Burks, and Verhoogen, 2005), Public Goods games (Andreoni, 1988 and 1995; Fehr and Gächter, 2000), the Keynesian Beauty Contest/Guessing Game (Ho, Camerer, and Weigelt, 1998), or the Minimum Effort Game (Van Huyck, Battalio, and Beil, 1990; Knez and Camerer, 1994; Bornstein, Gneezy, and Nagel, 2002; Devetag, 2005), compared to subjects in the lab. Likewise, Greiner, Caravella, and Roth (2014) also replicate Ultimatum Game experiments in Second Life and find the same qualitative results. Duffy (2011), on the other hand, highlights the weaknesses of using virtual worlds for lab experiments that may put into question its validity. On top of the standard problems associated with running experiments online (issues of reliability, recruitment, screening, retention, credibility, to name a few), Duffy stresses that using experimental design meant for subjects in the real world may not be appropriate, especially since players doing an experiment may not be sure whether the questions are directed toward the players' "roleplayed" characters or to their real-world selves. Crucially, he suggests that lab experiments in virtual worlds ought "to embed as many features of the virtual world in the experimental intervention as possible so

[23]For a more complete literature review, see Innocenti (2017).

that the experimental intervention (i) makes maximal use of the virtual environment in which participants interact with one another and (ii) minimizes the fact that an experiment is being conducted." Random assignment of locations turns out to be a common feature of many online communities that play Minecraft, presumably because in games with low population density, it provides a fast way for players to find unclaimed natural resources to exploit.[24] Therefore, it would not seem likely that the results of this paper should be particularly affected by experimenter bias or that players would even have reasons to be confused as to whether the game is eliciting their behavior as to how they should behave outside of the game or within it. The main challenge to this paper's external validity then, it would seem, is (i) whether Minecraft is an appropriate environment for studying early economic development, and (ii) whether the players that I study are representative of a more general population. I argue the case for (i) in section 4.1 by showing the different ways in which Stoneworks Minecraft resembles a standard economy. The game not only has many features which are intended to simulate important properties of the economy, including scarcity, property rights, and money, but it is also clear that the statistical properties of standard economic indicators are similar to those found in the real world.

The case for (ii) is only briefly made at the end of section 2.2 and thus elaborated further here. As I mentioned, there is suggestive evidence that the majority of the study's players are young men: Figure A2 in the Appendix shows the estimated age and gender distribution from YouTube's viewer analytics. [25] While there is no official source for the demographics data of Minecraft players more generally, Stoneworks viewers appear to skew male more than the standard Minecraft player. According to third-party estimates (Demandsage.com), around 54% of Minecraft players are male compared to Stonework viewers' 93%. If the viewer data is representative of those who actually play the game, this certainly limits the scope of the paper in extrapolating the results of my paper to a more gender-balanced popula-

[24]The three largest Minecraft communities with survival gamemodes (DonutSMP, Minehut, and Wynncraft) according to Minetrack.me all have either the same random assignment feature or a similar one. The word *gamemode* refers to a version of Minecraft with a particular set of rules.

[25]YouTube estimates age and gender of a YouTube user by comparing viewing history from users without a specified gender to the viewing history of users with a specified one. This implies that if age or gender is a predictor for specifying the information to YouTube, the estimates are biased.

tion.

One of the main channels through which inequality could be affected is via individual and social preferences (Fehr and Charness, 2025). If young men behave very differently than the general population with regard to social preferences, this may lead to very different predictions for the type of inequality that would emerge in my study if the study sample was more representative of a general population. Despite commonly held beliefs that women tend to be more generous and care more about equality, Exley et al. (2025) find that there is "little to no" experimental "evidence for gender differences in behavior or attitudes relating to social preferences."[26] Likewise, there is mixed experimental evidence for differences in prosocial behavior by age (Kettner and Waichman, 2016). Absent collecting more information from players in Stoneworks Minecraft, this by no means rules out the possibility that results are sensitive to the sample of players studied, but it does help narrow down *which* dimensions of the sample are most likely to matter. For instance, even if social preferences may not differ to that of the general population, there could be differences in other preferences that could be relevant to how inequality emerged in the study. Across different countries around the world, there is survey evidence from Falk et al. (2018) which shows that men tend to score higher (relative to women) in patience, risk-taking, and reciprocating punishment. At the same time, men score lower in altruism, trust, and reciprocating help. They also find that risk taking generally decreases with age, but patience and reciprocating help both have inverse-U shape relationships with respect to age (increasing up until age 24 and age 43 respectively, and then decreasing). If any of these preferences could cause differences in how players organize themselves in Minecraft, this could also affect my results. Even if none of these variables were to have an effect, there remains the possibility that the results of the paper may not generalize to a more representative study for reasons that are intrinsic to Stoneworks Minecraft, especially if Stoneworks players form part of a particular culture which is different to other young men and thus likely to produce differences in how affected they are by different location features.

[26] Exley et al. do point out in a footnote, however, that there is evidence which shows women are "more socially oriented than men in some contexts, such as mothers providing more childcare (Aguiar and Hurst 2007) and women being more left-leaning (Bertrand 2011)."

6 Conclusion

Inequality has become a central topic in economics, especially as the public discourse has centered around the causes of its persistence and rise around the world, the effect that it could have on political institutions and economic growth, and which policies, if any, should be taken to address it. However, the origins and causes of inequality have been less discussed and, in so far as it can be studied with regards to early economic development, it has been relegated to the work of studying archaeological and ethnographic records as well as developing economic theories.

This paper contributes to this literature by providing both a dataset and a method for studying the causal effect of initial environmental and economic conditions on economic inequality and, more broadly, economic development. By taking advantage of real-time video game data from a large online community and the random assignment of players to different locations, I provide causal evidence for historical theories of how inequality emerges. I show that exposure to capital intensity and appropriability in food production, together as opposed to separately, cause a significant increase in the level of income and (especially) wealth inequality within groups. This increase in inequality is driven by increases in the top earners of the wealth distribution within groups at the apparent cost of decreases for the bottom earners, which is consistent with the appropriability literature in political economy.

This paper highlights the potential of virtual worlds in video games in providing researchers ample ground for new experimentation as well as new sources of data. The natural experiment which forms the basis for causal inference in this paper relies on a "design" which suffers from several challenges, namely, potential omitted variable bias from bundled treatments and generalizability problems from a highly skewed sample population. Future research could take advantage of the strengths of Minecraft in emulating early economic development and iterate on these weaknesses by controlling the location assignment to ensure that there are no unobservable location features and by careful recruitment of participants into the game. Likewise, Stoneworks Minecraft specifically could also shed light into questions in other fields outside of comparative economic development, especially the role of conflict in economic development, how teams allocate and organize resources compared to individual players, and other questions which can take advantage of large complex economic data environments.

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Appendix

A Tables

Table A1: Properties of Minecraft Food Sources

Food Source	Nutritional Value	Appropriable	Craft	# Inputs	Renewable	Requires Farmland
Apple	6.4	✓	✗	0	✓	✗
Baked Potato	11	✗	✓	1	✓	✓
Beetroot	2.2	✓	✗	0	✓	✓
Beetroot Soup	13.2	✗	✓	2	✓	✓
Bread	11	✗	✓	1	✓	✓
Cake	2.4	✓	✓	4	✓	✓
Carrot	6.6	✓	✗	0	✓	✓
Chorus Fruit	6.4	✗	✗	0	✗	✗
Cooked Chicken	13.2	✗	✓	1	✓	✗
Cooked Cod	11	✗	✓	1	✗	✗
Cooked Mutton	15.6	✗	✓	1	✓	✗
Cooked Porkchop	20.8	✗	✓	1	✓	✗
Cooked Rabbit	11	✗	✓	1	✓	✗
Cooked Salmon	15.6	✗	✓	1	✗	✗
Cookie	2.4	✗	✓	2	✓	✓
Dried Kelp	1.6	✗	✓	1	✗	✗
Enchanted Golden Apple	13.6	✗	✓	3	✗	✗
Golden Apple	13.6	✗	✓	2	✗	✗
Glow Berries	2.4	✓	✗	0	✓	✗
Golden Carrot	20.4	✗	✓	2	✗	✓
Honey Bottle	7.2	✓	✓	1	✓	✗
Melon Slice	3.2	✓	✗	0	✓	✓
Mushroom Stew	13.2	✗	✓	3	✗	✗
Poisonous Potato	3.2	✓	✗	0	✓	✓
Potato	1.6	✓	✗	0	✓	✓
Pufferfish	1.2	✗	✓	1	✗	✗
Pumpkin Pie	12.8	✗	✓	3	✓	✓
Rabbit Stew	22	✗	✓	5	✗	✓
Beef	4.8	✓	✗	0	✓	✗
Chicken	3.2	✓	✗	0	✓	✗
Cod	2.4	✗	✗	0	✗	✗
Mutton	3.2	✓	✗	0	✓	✗
Porkchop	4.8	✓	✗	0	✓	✗
Rabbit	4.8	✓	✗	0	✓	✗
Salmon	2.4	✗	✗	0	✗	✗
Rotten Flesh	4.8	✓	✗	0	✓	✗
Spider Eye	5.2	✓	✗	0	✓	✗
Cooked Beef	20.8	✗	✓	1	✓	✗
Suspicious Stew	13.2	✗	✓	4	✗	✗
Sweet Berries	2.4	✓	✗	0	✓	✗
Tropical Fish	1.2	✗	✗	0	✗	✗

Table A2: Within-Group Inequality, Appropriability, and Land Dependence

	Income Gini (1)	Income Gini (2)	Wealth Gini (3)	Wealth Gini (4)
β_{App}	0.009	0.004	0.015*	0.072***
	(0.008)	(0.022)	(0.007)	(0.015)
β_{Land}	0.002	0.001	0.005	0.017***
	(0.004)	(0.006)	(0.003)	(0.005)
$\beta_{\text{App}\times\text{Land}}$		0.006		−0.074***
		(0.025)		(0.021)
Cohort FEs	Yes	Yes	Yes	Yes
Decomposed Food	No	No	No	No
Controls	Yes	Yes	Yes	Yes
Interactions	No	Yes	No	Yes
Observations	6,808	6,808	22,304	22,304
Minimum groups per period	35	35	64	64
Median groups per period	69	69	252	252
Maximum groups per period	143	143	386	386
R squared	0.178	0.180	0.145	0.151
Mean dep. var.	0.039	0.039	0.608	0.608

Notes: The table presents results from regressions of the within-group Gini coefficients of spatially clustered groups in a day (by HDBSCAN) on the share of food gain from appropriable foods (App), the share from land-dependent foods (Land), and interactions of those food shares in the same day. Controls include the inverse hyperbolic sine (IHS) of total group income for the income Gini, the IHS of total group wealth for the wealth Gini, and IHS of total food gain for both. Standard errors are robust to serial dependence (Driscoll and Kraay, 1998). Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3: Summary Statistics of Daily Player Activity Metrics

	Count	Mean	SD	Min	P25	Median	P75	Max	Inc.	Stay	Dec.
Playtime (hours)	24217	1.53	1.92	0.00	0.22	0.82	2.10	20.37	0.49	0.00	0.51
Market Sales (k S$)	14173	10.94	113.98	0.00	0.00	0.21	4.70	22284.20	0.37	0.25	0.37
Received Transfers (k S$)*	3470	5.3e+23	7.3e+25	0.00	0.20	2.50	12.40	1e+28	0.49	0.03	0.48
Taxes Collected (k S$)*	1885	4.74	217.14	0.00	0.00	0.00	0.00	55060.00	0.04	0.91	0.04
Income (k S$)*	5985	75.49	755.08	0.00	2.50	10.00	37.45	55121.03	0.50	0.00	0.49
Income / Playtime *	6483	29.91	449.09	0.00	0.64	2.72	10.43	34089.62	0.49	0.00	0.51
Market Purchases (k S$)	11327	5.83	35.49	0.00	0.00	0.36	2.65	4000.00	0.40	0.18	0.42
Sent Transfers (k S$)*	3839	6e+22	2.4e+25	0.00	0.00	0.00	0.00	1e+28	0.10	0.79	0.10
Taxes Paid (k S$)*	1388	4.86	320.62	0.00	0.00	0.00	0.00	120000.00	0.04	0.93	0.04
Expenses (k S$)*	13447	28.77	682.26	0.00	0.00	1.00	6.16	120003.12	0.45	0.10	0.45
Wealth (k S$)*	9155	35.55	964.78	-15200.13	0.00	0.00	0.19	55194.83	0.04	0.93	0.03
$\min\{\text{Wealth}, 0\}$ (k S$)*	2343	-16.09	254.48	-15200.13	0.00	0.00	0.00	0.00	0.01	0.98	0.01
$\max\{\text{Wealth}, 0\}$ (k S$)*	6813	51.64	929.72	0.00	0.00	0.00	0.19	55194.83	0.03	0.95	0.02
Commands in Land Mgmt*	291	8.79	19.48	0.00	1.00	3.00	10.00	2773.00	0.42	0.16	0.43
Commands in Nation Mgmt*	84	0.42	2.36	0.00	0.00	0.00	0.00	182.00	0.09	0.82	0.09
Total Commands*	701	31.78	74.54	1.00	5.00	14.00	36.00	15906.00	0.47	0.04	0.49
Land Claims Made*	135	0.28	4.03	0.00	0.00	0.00	0.00	474.00	0.03	0.94	0.03
Land Claims Given*	17	0.12	0.61	0.00	0.00	0.00	0.00	26.00	0.03	0.94	0.03
Picked Up Items	16481	2540.17	7336.01	0.00	40.00	446.00	2193.00	495721.00	0.49	0.01	0.50
Dropped Items	7833	612.11	2638.19	0.00	1.00	18.00	242.00	217659.00	0.45	0.09	0.46
Picked Up Food Items	3342	140.27	1239.95	0.00	0.00	1.00	32.00	136504.00	0.36	0.28	0.36
Dropped Food Items	1178	25.86	483.29	0.00	0.00	0.00	1.00	77152.00	0.24	0.51	0.25
Crafted Food Items	788	8.65	92.33	0.00	0.00	0.00	0.00	13568.00	0.09	0.82	0.09
Market Sales in Food (k S$)	2020	0.86	11.32	0.00	0.00	0.00	0.00	660.41	0.06	0.88	0.06
Market Purchases in Food (k S$)	1119	0.14	4.03	0.00	0.00	0.00	0.00	500.00	0.10	0.80	0.10
Food Items Used as Input	928	18.55	371.81	0.00	0.00	0.00	0.00	53532.00	0.03	0.94	0.03
Picked Up Food (Nutritional Value)	16408	425.72	4403.99	0.00	0.00	0.00	70.40	901857.40	0.29	0.41	0.30
Dropped Food (Nutritional Value)	7480	171.03	4305.96	0.00	0.00	0.00	0.00	834835.20	0.19	0.61	0.19
Purchased Food (Nutritional Value)	1397	130.33	5553.69	0.00	0.00	0.00	0.00	1064844.40	0.03	0.94	0.03
Sold Food (Nutritional Value)	1708	50.54	1546.09	0.00	0.00	0.00	0.00	351296.00	0.01	0.97	0.01
Crafted Food (Nutritional Value)	1661	48.71	393.77	0.00	0.00	0.00	0.00	60998.40	0.07	0.86	0.07
Food Used as Input (Nutritional Value)	1324	57.55	1064.01	0.00	0.00	0.00	0.00	99648.00	0.02	0.95	0.02
Periods	99										
# Players	20,961	2130.35	261.20	1649	1922	2077	2342	2806	0.48	0	0.52

Monetary variables are expressed in thousands of S$, rounded to two decimals.
Columns "Inc.", "Stay", and "Dec." report the probability a variable increases, stays constant, or decreases from period $t-1$ to t.
* Subject to measurement error (data only records attempts, not outcomes)

Table A4: Summary Statistics of Daily Group Activity Metrics

	Count	Mean	SD	Min	P25	Median	P75	Max
Group Size	16	3.01	1.35	2.00	2.00	3.00	4.00	19.00
Group Income / Group Size (k S$) *	5230	26.88	238.04	0.00	0.88	3.58	13.66	17425.00
Group Wealth / Group Size (k S$) *	17076	57.04	565.09	0.00	0.00	1.21	17.89	27571.98
Income Gini *	808	0.04	0.12	0.00	0.00	0.00	0.00	0.75
Bottom Income Within Group (k S$) *	4551	64.97	520.52	0.00	2.00	8.90	32.45	34850.00
20th Income Percentile Within Group (k S$) *	4922	66.95	520.95	0.00	2.51	10.00	35.35	34850.00
Median Income Within Group (k S$) *	4853	69.92	523.70	0.00	2.75	10.10	38.34	34850.00
70th Income Percentile Within Group (k S$) *	4958	72.07	526.99	0.00	2.82	10.44	39.87	34850.00
Top Income Within Group (k S$) *	4705	76.18	541.79	0.00	2.90	10.70	40.80	34850.00
P90/P50 of Income Within Group *	815	1.28	16.45	1.00	1.00	1.00	1.00	1400.80
P90/P10 of Income Within Group *	817	2.09	41.90	1.00	1.00	1.00	1.00	3494.34
Top Income Within Group / Group Income *	808	0.98	0.08	0.39	1.00	1.00	1.00	1.00
Wealth Gini *	13391	1.27	35.45	0.00	0.50	0.66	0.75	5917.18
$\max\{\text{Wealth}, 0\}$ Gini *	8735	0.60	0.15	0.00	0.50	0.63	0.70	0.92
$\min\{\text{Wealth}, 0\}$ Gini *	1395	0.64	0.13	0.00	0.50	0.67	0.75	0.93
Bottom $\max\{\text{Wealth}, 0\}$ Within Group (k S$) *	1462	1.40	18.19	0.00	0.00	0.00	0.00	1625.53
20th $\max\{\text{Wealth}, 0\}$ Percentile Within Group (k S$) *	7558	12.02	168.01	0.00	0.00	0.00	0.64	11066.56
Median $\max\{\text{Wealth}, 0\}$ Within Group (k S$) *	7829	28.69	416.26	0.00	0.00	0.00	3.28	27571.98
70th $\max\{\text{Wealth}, 0\}$ Percentile Within Group (k S$) *	15648	61.75	691.54	0.00	0.00	0.46	16.62	38575.60
Top $\max\{\text{Wealth}, 0\}$ Within Group (k S$) *	5721	163.73	1639.71	0.00	0.00	3.40	47.30	55194.83
P90/P50 of $\max\{\text{Wealth}, 0\}$ Within Group *	7112	568.18	36473.29	1.00	1.80	1.80	3.67	4240004.46
P90/P10 of $\max\{\text{Wealth}, 0\}$ Within Group *	4984	339.35	7711.58	1.00	9.00	9.00	9.00	474821.00
Top $\max\{\text{Wealth}, 0\}$ Within Group / Group $\max\{\text{Wealth}, 0\}$ *	8112	0.93	0.13	0.26	0.94	1.00	1.00	1.00
Bottom Tenure Within Group	91	20.97	23.70	0.00	2.00	11.00	35.00	90.00
20th Tenure Percentile Within Group	1386	26.60	22.94	0.00	7.60	20.00	41.00	91.00
Median Tenure Percentile Within Group	184	34.16	24.40	0.00	13.00	30.50	52.50	94.00
70th Tenure Percentile Within Group	2761	37.71	24.61	0.00	16.00	35.10	57.40	95.00
Top Tenure Within Group	98	42.19	26.13	0.00	19.00	41.00	65.00	98.00
% of Random Players	50	0.79	0.28	0.00	0.50	1.00	1.00	1.00

This table reports summary statistics for cross sections of spatially clustered groups of players (by HDBSCAN) in a day.
Monetary variables, expressed in thousands of S$, rounded to two decimals.
* Subject to measurement error (data only records attempts, not outcomes)

Table A5: Identified Randomly Assigned Players vs. Others (After Cohort FE)

	I_R			I_S			$I_R - I_S$	
	Count	Mean	SD	Count	Mean	SD	Adj. Difference	
Playtime (hours)	22444	1.58	1.94	12278	1.34	1.80	-0.039	(0.034)
Market Sales (k S$)	9654	11.57	64.95	4162	6.86	33.90	0.911	(1.107)
Received Transfers (k S$)*	2953	708.44	80707.12	890	3.0e+24	1.7e+26	1603.15	(1722.10)
Taxes Collected (k S$)*	1772	4.98	207.35	243	3.83	252.47	-2.27	(2.87)
Income (k S$)*	4632	86.62	847.57	1457	33.07	178.12	$32.88^{**,rrr}$	(11.15)
Income / Playtime (k S$)*	4847	33.35	512.92	1372	15.32	81.96	9.87^{*}	(5.23)
Market Purchases (k S$)	8533	6.48	39.73	2918	3.45	21.34	0.788	(0.695)
Sent Transfers (k S$)*	3271	7.8e+22	2.8e+25	986	2.12	73.73	1.97e+23	(1.79e+23)
Taxes Paid (k S$) *	1244	5.59	359.79	277	2.33	109.48	-0.749	(1.990)
Expenses (k S$)*	10962	33.04	756.65	3329	15.24	316.26	0.830	(11.63)
Wealth (k S$) *	7039	43.89	1099.36	1880	3.46	256.60	25.66	(16.22)
$\min\{\text{Wealth}, 0\}$ (k S$)*	1919	-19.33	267.17	393	-7.70	234.64	6.92	(15.72)
$\max\{\text{Wealth}, 0\}$ (k S$) *	5121	63.22	1065.26	1488	11.16	103.03	18.74	(16.84)
Land Mgmt Commands *	284	9.79	21.06	148	5.22	12.22	$0.0466^{***,rrr}$	(0.0091)
Nation Mgmt Commands *	73	0.45	2.29	54	0.30	2.66	$0.00306^{***,rrr}$	(0.00087)
Total Commands*	690	34.10	80.32	336	22.86	37.35	2.10	(1.38)
Claims Made *	131	0.32	4.43	57	0.13	2.33	$0.0885^{***,rrr}$	(0.0194)
Claims Given*	16	0.13	0.62	10	0.10	0.56	$0.0526^{***,rrr}$	(0.0116)
Items Picked Up	15043	2647.26	7793.01	7119	2073.79	5258.30	121.59	(104.81)
Items Dropped	7160	657.14	2836.84	3057	420.42	1684.69	$108.69^{*,r}$	(42.61)
Food Items Picked Up	2878	134.21	1230.51	1701	160.45	1335.71	$-28.75^{**,rr}$	(9.03)
Food Items Dropped	1055	26.50	504.50	521	23.94	428.68	0.523	(2.24)
Food Items Crafted	707	8.60	99.36	348	8.67	63.69	-0.572	(0.667)
Food Sales	1485	1033.16	12483.13	592	343.79	5568.42	118.66	(90.77)
Food Purchases	794	157.90	4764.34	424	106.63	1501.83	17.55	(35.60)
Food Items Used as Input	832	19.88	379.93	298	14.79	358.97	-3.24^{*}	(1.67)
Food Pickups (n.v.)	13352	425.20	4055.50	6549	457.75	5771.43	$-86.46^{***,rr}$	(21.90)
Food Dropped (n.v.)	6334	181.86	4492.57	2494	153.87	4071.78	0.315	(17.68)
Food Purchased (n.v.)	1012	140.93	6329.10	484	70.71	1879.57	-2.56	(18.46)
Food Sold (n.v.)	1269	51.44	1693.60	550	38.07	673.36	-0.247	(6.93)
Food Crafted (n.v.)	1356	45.75	408.31	663	60.66	330.16	$-11.66^{**,rrr}$	(3.91)
Food Used as Input (n.v.)	1144	65.80	1121.50	432	38.47	958.20	-8.69^{*}	(4.94)
# of Players	9951			9863				

* Subject to measurement error (data only records attempts, not outcomes). Monetary variables are expressed in thousands of S$, rounded to two decimals. Romano-Wolf adjusted p-values are calculated using the estimated coefficients in this table alone.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. (Romano-Wolf Adjusted: ^{r} $p^{RW} < 0.05$, ^{rr} $p^{RW} < 0.01$, ^{rrr} $p^{RW} < 0.001$).

Table A6: Within-Group Income Ineq. and I_R Location Features(+Interactions)

	Inc. Gini (1)	IHS(P10) (2)	IHS(P50) (3)	IHS(P90) (4)	IHS(G.Inc.) (5)	log(G.Size) (6)
γ_{Capital}	−0.164	−4.960	−5.233	−5.528	−5.883	−0.282**
	(0.225)	(5.670)	(5.582)	(5.558)	(5.562)	(0.087)
γ_{App}	0.150	1.212	1.655	1.807	1.854	0.255*
	(0.094)	(2.682)	(2.582)	(2.539)	(2.512)	(0.098)
γ_{Renew}	0.033	0.106	0.192	0.242	0.263	$0.083^{***,rr}$
	(0.018)	(0.631)	(0.616)	(0.610)	(0.604)	(0.021)
γ_{Land}	0.114	1.061	1.315	1.527	1.638	$0.476^{***,rrr}$
	(0.070)	(2.203)	(2.196)	(2.179)	(2.183)	(0.053)
$\gamma_{\text{Capital}\times\text{App}}$	0.067	0.484	0.542	0.623	0.859	$0.938^{***,rrr}$
	(0.179)	(2.638)	(2.720)	(2.772)	(2.768)	(0.193)
$\gamma_{\text{Capital}\times\text{Renew}}$	0.276	5.607	6.247	6.657	7.023	$0.437^{***,rr}$
	(0.268)	(6.082)	(6.101)	(6.137)	(6.182)	(0.114)
$\gamma_{\text{Capital}\times\text{Land}}$	−0.108	−1.227	−1.572	−1.681	−1.668	−0.168**
	(0.099)	(1.009)	(1.181)	(1.266)	(1.295)	(0.057)
$\gamma_{\text{App}\times\text{Renew}}$	−0.193	−1.581	−2.108	−2.358	−2.472	−0.244*
	(0.098)	(2.951)	(2.853)	(2.811)	(2.783)	(0.101)
$\gamma_{\text{App}\times\text{Land}}$	0.006	0.416	0.400	0.464	0.525	0.034
	(0.045)	(1.131)	(1.151)	(1.172)	(1.182)	(0.042)
$\gamma_{\text{Renew}\times\text{Land}}$	−0.118	−0.910	−1.166	−1.402	−1.530	$-0.433^{***,rrr}$
	(0.068)	(2.252)	(2.231)	(2.207)	(2.206)	(0.055)
$\gamma_{\text{Tax Rate}}$	0.005	−2.717*	−2.703*	−2.677*	−2.711*	$-0.642^{***,rrr}$
	(0.051)	(1.092)	(1.108)	(1.115)	(1.119)	(0.041)
$\gamma_{\text{Income Gini}}$	0.087	−4.552	−4.255	−4.131	−4.202	−0.002
	(0.134)	(3.248)	(3.347)	(3.392)	(3.420)	(0.093)
$\gamma_{\text{Wealth Gini}}$	−0.017	0.749	0.736	0.688	0.646	$-0.292^{***,rrr}$
	(0.026)	(0.625)	(0.641)	(0.648)	(0.649)	(0.020)
Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Decomposed Food	No	No	No	No	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,197	2,218	2,218	2,218	2,218	14,556
Cohorts	361	362	362	362	362	1,110
Min. groups/per.	102	102	102	102	102	102
Med. groups/per.	159	159	159	159	159	159
Max. groups/per.	272	272	272	272	272	272
R squared	0.169	0.234	0.236	0.236	0.236	0.271
Mean (raw) dep. var.	0.039	65,960	69,916	74,814	78,015	3.008

Notes: The table presents results from regressions of the within-group outcomes of spatially clustered groups in a day (by HDBSCAN) on aggregate starting location features for randomly assigned members of the group. The outcomes include the within-group income Gini coefficient (Inc. Gini), the within-group income percentiles (P10, P50, P90), the sum of all income within the group (G. Inc.), and the number of players within a group (G.Size). The features include the average share of food gain from crafted foods (Capital), appropriable foods (App), renewable foods (Renew), and land-dependent foods (Land) of the players surrounding the starting locations of randomly assigned group members; the average share of expenses in tax payments (Tax Rate) of players surrounding the starting locations of randomly assigned group members; the average within-group Gini coefficient in income (Income Gini) and wealth (Wealth Gini) of players surrounding the starting locations of randomly assigned group members. Controls include other starting location features (see section C), including variables related to resource type distributions, population density, food surplus, share of income in tax collection, market penetration, land/nation management, land claims, town invitations, town creation, arrows shot, share of items collected in food, share of randomly assigned players, average tenure and playtime, transfer payments, and existing income/wealth levels. Standard errors are robust to serial dependence (Driscoll and Kraay, 1998), Romano-Wolf p-value adjustment accounts for hypothesis testing in Table 7, 8, and 9. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. (Romano-Wolf Adjusted: ^{r} $p^{RW} < 0.05$, ^{rr} $p^{RW} < 0.01$, ^{rrr} $p^{RW} < 0.001$).

Table A7:

	lhs: income_construct_gini	lhs: asinh(income_construct_p10)	lhs: asinh(income_construct_p50)	lhs: asinh(income_construct_p90)	lhs: asinh(income_construct_sum)
initial_peer_app_farm_renew_food_create_pts_prop_lag1_mean	−0.136	−2.801	−3.173	−3.366	−3.473
	(0.100)	(2.453)	(2.304)	(2.218)	(2.124)
initial_peer_app_nonfarm_renew_food_create_pts_prop_lag1_mean	0.568*	0.586	2.345	3.036	3.140
	(0.269)	(2.832)	(3.069)	(3.220)	(3.257)
initial_peer_nonapp_farm_renew_food_create_pts_prop_lag1_mean	−0.025	0.557	0.480	0.463	0.459
	(0.018)	(0.356)	(0.356)	(0.357)	(0.356)
initial_peer_nonapp_farm_nonrenew_food_create_pts_prop_lag1_mean	0.025	0.161	0.182	0.235	0.304
	(0.052)	(0.896)	(0.873)	(0.880)	(0.886)
initial_peer_nonapp_nonfarm_renew_food_create_pts_prop_lag1_mean	0.311	4.828*	5.761**	6.158**	6.229**
	(0.187)	(2.249)	(1.951)	(1.899)	(1.880)
initial_peer_app_farm_renew_food_destroy_pts_prop_lag1_mean	0.017	0.057	0.101	0.132	0.148
	(0.019)	(0.374)	(0.381)	(0.385)	(0.389)
initial_peer_app_nonfarm_renew_food_destroy_pts_prop_lag1_mean	−0.014	0.026	−0.008	−0.031	−0.084
	(0.028)	(0.678)	(0.682)	(0.680)	(0.680)
initial_peer_nonapp_farm_renew_food_destroy_pts_prop_lag1_mean	−0.100	−54.345*	−54.535*	−55.210*	−55.151*
	(0.837)	(22.337)	(23.017)	(23.367)	(23.526)
initial_peer_app_farm_renew_food_pickup_pts_prop_lag1_mean	0.002	0.409	0.404	0.389	0.410
	(0.017)	(0.340)	(0.344)	(0.351)	(0.358)
initial_peer_app_nonfarm_renew_food_pickup_pts_prop_lag1_mean	−0.001	0.459+	0.454+	0.451+	0.458+
	(0.013)	(0.256)	(0.257)	(0.261)	(0.263)
initial_peer_nonapp_farm_renew_food_pickup_pts_prop_lag1_mean	0.003	0.770*	0.789*	0.768*	0.757*
	(0.013)	(0.306)	(0.302)	(0.307)	(0.310)
initial_peer_nonapp_farm_nonrenew_food_pickup_pts_prop_lag1_mean	0.387	5.590	6.951	7.357	7.273
	(0.607)	(5.660)	(5.337)	(5.377)	(5.314)
initial_peer_nonapp_nonfarm_renew_food_pickup_pts_prop_lag1_mean	0.009	1.245*	1.276*	1.273*	1.265*
	(0.025)	(0.626)	(0.617)	(0.609)	(0.608)
initial_peer_app_farm_renew_food_drop_pts_prop_lag1_mean	−0.020	−1.331*	−1.362*	−1.431*	−1.467*
	(0.025)	(0.608)	(0.579)	(0.572)	(0.573)
initial_peer_app_nonfarm_renew_food_drop_pts_prop_lag1_mean	0.028	0.024	0.118	0.113	0.103
	(0.017)	(0.383)	(0.383)	(0.382)	(0.382)
initial_peer_nonapp_farm_renew_food_drop_pts_prop_lag1_mean	−0.008	−0.606+	−0.621+	−0.659+	−0.683+
	(0.018)	(0.321)	(0.335)	(0.345)	(0.348)
initial_peer_nonapp_farm_nonrenew_food_drop_pts_prop_lag1_mean	−0.240	4.187	3.571	3.173	2.929
	(0.149)	(2.672)	(2.803)	(2.908)	(2.961)
initial_peer_nonapp_nonfarm_renew_food_drop_pts_prop_lag1_mean	−0.025	−0.410	−0.458	−0.512	−0.533
	(0.021)	(0.691)	(0.688)	(0.689)	(0.686)
initial_peer_app_farm_renew_food_sales_pts_prop_lag1_mean	0.016	0.628	0.673	0.654	0.670
	(0.030)	(0.548)	(0.545)	(0.555)	(0.557)
initial_peer_app_nonfarm_renew_food_sales_pts_prop_lag1_mean	−0.005	−0.532	−0.568	−0.604	−0.571
	(0.029)	(0.581)	(0.558)	(0.547)	(0.548)
initial_peer_nonapp_farm_renew_food_sales_pts_prop_lag1_mean	−0.045	0.915	0.791	0.681	0.648
	(0.033)	(0.751)	(0.738)	(0.734)	(0.731)
initial_peer_nonapp_nonfarm_renew_food_sales_pts_prop_lag1_mean	0.050	0.593	0.641	0.838	0.981
	(0.054)	(1.304)	(1.340)	(1.356)	(1.401)
initial_peer_app_farm_renew_food_purchases_pts_prop_lag1_mean	−0.007	−1.035	−1.036	−1.029	−1.017
	(0.059)	(1.354)	(1.350)	(1.354)	(1.366)
initial_peer_app_nonfarm_renew_food_purchases_pts_prop_lag1_mean	0.025	1.139	1.177	1.183	1.259
	(0.037)	(0.852)	(0.838)	(0.837)	(0.841)
initial_peer_nonapp_farm_renew_food_purchases_pts_prop_lag1_mean	−0.023	0.286	0.213	0.180	0.155
	(0.029)	(0.579)	(0.572)	(0.573)	(0.571)
initial_peer_nonapp_farm_nonrenew_food_purchases_pts_prop_lag1_mean	−0.431**	3.442	2.495	1.930	1.392
	(0.155)	(4.519)	(4.539)	(4.576)	(4.544)
initial_peer_nonapp_nonfarm_renew_food_purchases_pts_prop_lag1_mean	0.017	0.466	0.502	0.503	0.518
	(0.044)	(0.748)	(0.790)	(0.799)	(0.817)
initial_peer_food_create_pts_prop_lag1_mean	0.058+	−1.626*	−1.442*	−1.387*	−1.363*
	(0.031)	(0.620)	(0.612)	(0.610)	(0.610)
initial_peer_food_purchases_pts_prop_lag1_mean	0.037	−0.138	0.010	0.076	0.236
	(0.109)	(1.381)	(1.380)	(1.411)	(1.420)
initial_peer_food_sales_pts_prop_lag1_mean	−0.168*	1.692	1.240	1.018	0.799
	(0.083)	(2.064)	(2.038)	(2.035)	(2.050)
initial_peer_food_destroy_pts_prop_lag1_mean	−0.043	0.183	0.115	0.050	0.007
	(0.045)	(0.924)	(0.905)	(0.896)	(0.893)
initial_peer_food_drop_pts_prop_lag1_mean	−0.028	0.711+	0.627	0.606	0.590
	(0.017)	(0.388)	(0.387)	(0.389)	(0.390)
initial_peer_food_pickup_pts_prop_lag1_mean	0.010	−0.489+	−0.469	−0.436	−0.423
	(0.015)	(0.291)	(0.292)	(0.297)	(0.300)
Num.Obs.	5542	5590	5590	5590	5590
R2	0.150	0.154	0.154	0.154	0.153
FE: cohort_p100	X	X	X	X	X

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table A8:

	lhs: wealth_positive_gini	lhs: asinh(wealth_positive_p10)	lhs: asinh(wealth_positive_p50)	lhs: asinh(wealth_positive_p90)	lhs: asinh(wealth_positive_sum)
initial_peer_app_farm_renew_food_create_pts_prop_lag1_mean	−0.031	−1.833+	−3.040*	−4.623**	−4.910***
	(0.044)	(0.974)	(1.258)	(1.374)	(1.400)
initial_peer_app_nonfarm_renew_food_create_pts_prop_lag1_mean	0.013	−0.864	−0.682	−3.254*	−3.426*
	(0.050)	(1.009)	(1.211)	(1.583)	(1.648)
initial_peer_nonapp_farm_renew_food_create_pts_prop_lag1_mean	−0.019*	0.199	0.240	−0.105	−0.131
	(0.008)	(0.163)	(0.192)	(0.268)	(0.274)
initial_peer_nonapp_farm_nonrenew_food_create_pts_prop_lag1_mean	0.013	−1.562**	−1.651*	−1.769*	−1.815*
	(0.023)	(0.553)	(0.673)	(0.790)	(0.813)
initial_peer_nonapp_nonfarm_renew_food_create_pts_prop_lag1_mean	−0.073	6.453**	7.521**	11.191***	11.361***
	(0.072)	(2.290)	(2.620)	(1.674)	(1.728)
initial_peer_app_farm_renew_food_destroy_pts_prop_lag1_mean	−0.058***	1.248***	1.322***	0.927*	0.924*
	(0.013)	(0.297)	(0.317)	(0.395)	(0.409)
initial_peer_app_nonfarm_renew_food_destroy_pts_prop_lag1_mean	−0.028	0.045	−0.225	−1.128*	−1.189*
	(0.020)	(0.423)	(0.439)	(0.506)	(0.525)
initial_peer_nonapp_farm_renew_food_destroy_pts_prop_lag1_mean	−1.829***	16.328+	14.249	−15.674	−16.825
	(0.455)	(8.463)	(9.804)	(10.625)	(11.101)
initial_peer_app_farm_renew_food_pickup_pts_prop_lag1_mean	−0.062***	1.096***	1.143***	0.215	0.178
	(0.012)	(0.266)	(0.306)	(0.300)	(0.302)
initial_peer_app_nonfarm_renew_food_pickup_pts_prop_lag1_mean	−0.007	−0.048	−0.196	−0.799**	−0.832**
	(0.008)	(0.187)	(0.212)	(0.258)	(0.261)
initial_peer_nonapp_farm_renew_food_pickup_pts_prop_lag1_mean	−0.059***	1.450***	1.623***	1.000***	0.993***
	(0.012)	(0.239)	(0.265)	(0.249)	(0.251)
initial_peer_nonapp_farm_nonrenew_food_pickup_pts_prop_lag1_mean	−0.289	8.409	8.392	19.920+	19.697+
	(0.282)	(9.391)	(12.191)	(11.621)	(11.826)
initial_peer_nonapp_nonfarm_renew_food_pickup_pts_prop_lag1_mean	−0.061***	1.637***	1.894***	1.392*	1.399*
	(0.015)	(0.345)	(0.458)	(0.575)	(0.589)
initial_peer_app_farm_renew_food_drop_pts_prop_lag1_mean	−0.046***	0.080	−0.261	−0.929**	−1.001**
	(0.012)	(0.296)	(0.364)	(0.350)	(0.353)
initial_peer_app_nonfarm_renew_food_drop_pts_prop_lag1_mean	−0.047***	0.913***	0.869***	0.367	0.301
	(0.011)	(0.209)	(0.227)	(0.291)	(0.301)
initial_peer_nonapp_farm_renew_food_drop_pts_prop_lag1_mean	−0.059***	0.116	−0.294	−1.666***	−1.801***
	(0.010)	(0.254)	(0.323)	(0.337)	(0.346)
initial_peer_nonapp_farm_nonrenew_food_drop_pts_prop_lag1_mean	0.271*	−9.215*	−11.441**	−14.112*	−14.683*
	(0.108)	(3.820)	(4.176)	(7.073)	(7.317)
initial_peer_nonapp_nonfarm_renew_food_drop_pts_prop_lag1_mean	−0.063***	0.410	0.347	−0.618	−0.695
	(0.015)	(0.297)	(0.401)	(0.507)	(0.520)
initial_peer_app_farm_renew_food_sales_pts_prop_lag1_mean	−0.053**	0.428	0.135	−1.257*	−1.369*
	(0.016)	(0.457)	(0.512)	(0.562)	(0.572)
initial_peer_app_nonfarm_renew_food_sales_pts_prop_lag1_mean	−0.100***	1.572*	1.260	−1.049	−1.156
	(0.022)	(0.676)	(0.780)	(0.839)	(0.862)
initial_peer_nonapp_farm_renew_food_sales_pts_prop_lag1_mean	−0.011	0.084	−0.088	−0.679	−0.773
	(0.017)	(0.440)	(0.554)	(0.609)	(0.628)
initial_peer_nonapp_nonfarm_renew_food_sales_pts_prop_lag1_mean	−0.011	−0.069	−0.027	−0.356	−0.365
	(0.027)	(0.722)	(0.847)	(0.947)	(0.988)
initial_peer_app_farm_renew_food_purchases_pts_prop_lag1_mean	0.019	0.079	0.125	−0.112	−0.192
	(0.029)	(0.565)	(0.639)	(0.560)	(0.568)
initial_peer_app_nonfarm_renew_food_purchases_pts_prop_lag1_mean	−0.061**	2.098***	2.434***	1.796*	1.715*
	(0.022)	(0.404)	(0.486)	(0.762)	(0.787)
initial_peer_nonapp_farm_renew_food_purchases_pts_prop_lag1_mean	−0.093***	2.090***	2.369***	1.419**	1.364**
	(0.012)	(0.313)	(0.369)	(0.481)	(0.501)
initial_peer_nonapp_farm_nonrenew_food_purchases_pts_prop_lag1_mean	−0.495*	14.873*	21.230***	14.551*	15.184*
	(0.240)	(5.850)	(6.047)	(6.130)	(6.384)
initial_peer_nonapp_nonfarm_renew_food_purchases_pts_prop_lag1_mean	−0.047**	1.929***	2.036***	1.885**	1.782**
	(0.016)	(0.431)	(0.493)	(0.624)	(0.636)
initial_peer_food_create_pts_prop_lag1_mean	0.002	−0.215	−0.290	−0.706	−0.699
	(0.022)	(0.383)	(0.457)	(0.450)	(0.467)
initial_peer_food_purchases_pts_prop_lag1_mean	−0.168**	0.924	1.570	0.127	0.082
	(0.051)	(1.091)	(1.297)	(1.141)	(1.178)
initial_peer_food_sales_pts_prop_lag1_mean	0.010	−1.020	−2.364	−1.359	−1.386
	(0.045)	(1.279)	(1.495)	(1.652)	(1.696)
initial_peer_food_destroy_pts_prop_lag1_mean	0.018	0.066	−0.230	−0.350	−0.416
	(0.019)	(0.501)	(0.521)	(0.846)	(0.874)
initial_peer_food_drop_pts_prop_lag1_mean	0.005	0.153	−0.067	−0.288	−0.310
	(0.009)	(0.228)	(0.254)	(0.251)	(0.258)
initial_peer_food_pickup_pts_prop_lag1_mean	−0.017*	−0.058	−0.092	−0.481*	−0.509*
	(0.008)	(0.201)	(0.218)	(0.229)	(0.233)
Num.Obs.	19 249	32 083	32 083	32 083	32 083
R2	0.294	0.177	0.173	0.233	0.237
FE: cohort_p100	X	X	X	X	X

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table A9:

	lhs: log(n_users)	lhs: asinh(town_deposit_sum_sum)
initial_peer_app_farm_renew_food_create_pts_prop_lag1_mean	−0.271**	−1.040*
	(0.083)	(0.516)
initial_peer_app_nonfarm_renew_food_create_pts_prop_lag1_mean	−0.330**	0.235
	(0.121)	(0.812)
initial_peer_nonapp_farm_renew_food_create_pts_prop_lag1_mean	−0.073***	0.008
	(0.016)	(0.117)
initial_peer_nonapp_farm_nonrenew_food_create_pts_prop_lag1_mean	−0.055	−0.470
	(0.058)	(0.416)
initial_peer_nonapp_nonfarm_renew_food_create_pts_prop_lag1_mean	0.028	2.994
	(0.082)	(1.954)
initial_peer_app_farm_renew_food_destroy_pts_prop_lag1_mean	−0.080**	0.083
	(0.024)	(0.225)
initial_peer_app_nonfarm_renew_food_destroy_pts_prop_lag1_mean	−0.115**	−0.373+
	(0.040)	(0.205)
initial_peer_nonapp_farm_renew_food_destroy_pts_prop_lag1_mean	−2.435***	−9.207
	(0.708)	(6.440)
initial_peer_app_farm_renew_food_pickup_pts_prop_lag1_mean	−0.110***	0.193
	(0.018)	(0.168)
initial_peer_app_nonfarm_renew_food_pickup_pts_prop_lag1_mean	−0.019	−0.055
	(0.016)	(0.109)
initial_peer_nonapp_farm_renew_food_pickup_pts_prop_lag1_mean	−0.085***	0.494***
	(0.019)	(0.138)
initial_peer_nonapp_farm_nonrenew_food_pickup_pts_prop_lag1_mean	−1.112+	−0.105
	(0.609)	(6.432)
initial_peer_nonapp_nonfarm_renew_food_pickup_pts_prop_lag1_mean	−0.094***	−0.064
	(0.027)	(0.212)
initial_peer_app_farm_renew_food_drop_pts_prop_lag1_mean	−0.157***	−0.553*
	(0.020)	(0.252)
initial_peer_app_nonfarm_renew_food_drop_pts_prop_lag1_mean	−0.155***	0.144
	(0.023)	(0.225)
initial_peer_nonapp_farm_renew_food_drop_pts_prop_lag1_mean	−0.230***	−0.805***
	(0.017)	(0.190)
initial_peer_nonapp_farm_nonrenew_food_drop_pts_prop_lag1_mean	0.042	−2.313
	(0.247)	(1.819)
initial_peer_nonapp_nonfarm_renew_food_drop_pts_prop_lag1_mean	−0.169***	−0.529+
	(0.024)	(0.271)
initial_peer_app_farm_renew_food_sales_pts_prop_lag1_mean	−0.149***	0.169
	(0.028)	(0.281)
initial_peer_app_nonfarm_renew_food_sales_pts_prop_lag1_mean	−0.202***	−0.329
	(0.044)	(0.339)
initial_peer_nonapp_farm_renew_food_sales_pts_prop_lag1_mean	−0.081*	0.170
	(0.038)	(0.353)
initial_peer_nonapp_nonfarm_renew_food_sales_pts_prop_lag1_mean	−0.081	−0.433
	(0.062)	(0.581)
initial_peer_app_farm_renew_food_purchases_pts_prop_lag1_mean	−0.045	−1.205**
	(0.057)	(0.421)
initial_peer_app_nonfarm_renew_food_purchases_pts_prop_lag1_mean	−0.169**	−0.002
	(0.056)	(0.593)
initial_peer_nonapp_farm_renew_food_purchases_pts_prop_lag1_mean	−0.157***	−0.452
	(0.032)	(0.310)
initial_peer_nonapp_farm_nonrenew_food_purchases_pts_prop_lag1_mean	−0.111	−0.994
	(0.488)	(3.964)
initial_peer_nonapp_nonfarm_renew_food_purchases_pts_prop_lag1_mean	−0.226***	0.692+
	(0.039)	(0.402)
initial_peer_food_create_pts_prop_lag1_mean	0.018	−0.249
	(0.046)	(0.298)
initial_peer_food_purchases_pts_prop_lag1_mean	−0.327***	0.618
	(0.094)	(0.961)
initial_peer_food_sales_pts_prop_lag1_mean	−0.186*	−0.573
	(0.093)	(0.653)
initial_peer_food_destroy_pts_prop_lag1_mean	−0.116*	−0.281
	(0.045)	(0.342)
initial_peer_food_drop_pts_prop_lag1_mean	−0.028+	−0.104
	(0.016)	(0.175)
initial_peer_food_pickup_pts_prop_lag1_mean	−0.072***	−0.485**
	(0.014)	(0.148)
Num.Obs.	32 083	32 029
R2	0.377	0.070
FE: cohort_p100	X	X

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Figure A1: Screenshots of Minecraft from a first-person (left) and a third-person perspective (right). In first-person, the player can only see their avatar's hands and the environment in front of them whereas in third-person, the player can see their entire avatar and what is immediately behind them.

B Additional figures

C List of location features

- **Share of resource type at the surface (water, dirt, terracotta, wood, sand, structures, ocean, snow, ice, stone, mycelium, lava, and farmland) surrounding a randomly assigned starting location (13 variables).**
- **Number of players surrounding a randomly assigned starting location. (1 variable).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged average share of food gain in capital-intensive, appropriable, renewable, and land dependent foods of players surrounding a randomly assigned starting location (4 variables).**
- **Lagged average level of food gain of players surrounding a randomly assigned starting location (1 variable).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged average share of income (expenses) in tax collection (payments) of players surrounding a randomly assigned starting location (2 variables).**

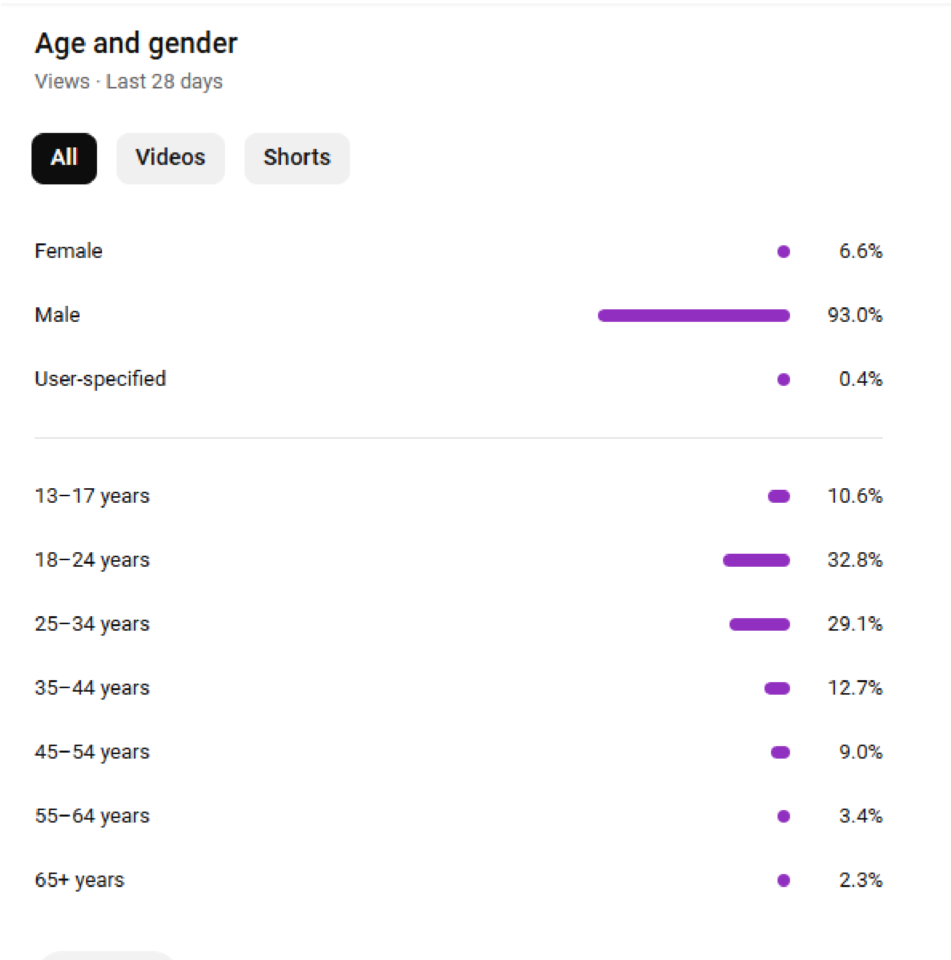

Figure A2: Estimated distribution of Stoneworks age and gender from viewer analytics as of July 19, 2025

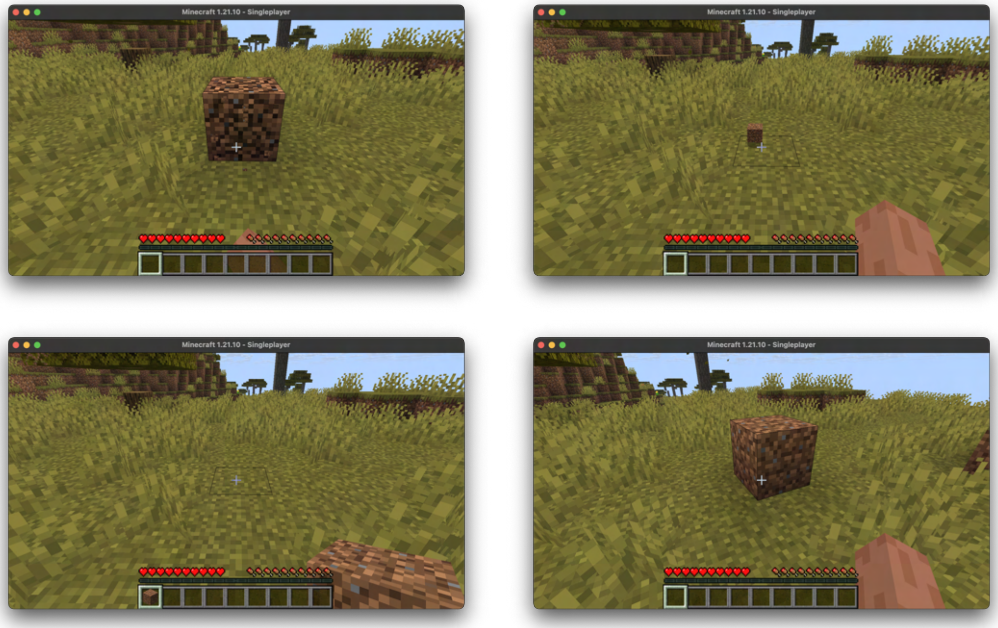

Figure A3: Screenshots before breaking a dirt block (top-left), immediately after breaking the dirt block but before picking up its drop (top-right), after picking up the dirt block (bottom-left), and after placing the dirt block (bottom-right).

- **Lagged average share of income (expenses) in market purchases (sales) of players surrounding a randomly assigned starting location (2 variables).**
- **Lagged average share of commands in land (nation) management of players surrounding a randomly assigned starting location (2 variables).**
- **Lagged median number of land claims of players surrounding a randomly assigned starting location (1 variable).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged median number of town invitations accepted (rejected) of players surrounding a randomly assigned starting location (2 variables).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged median number of towns created (deleted) of players surrounding a randomly assigned starting location (2 variables).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged average number of arrows fired of players surrounding a**

Figure A4: Screenshots of the stages of producing a chest in Minecraft. The first row is chopping down a tree, the second row is crafting wooden planks and then a crafting table, the third row is placing the crafting table and crafting a chest, and fourth row is placing two chests to make a large chest storage.

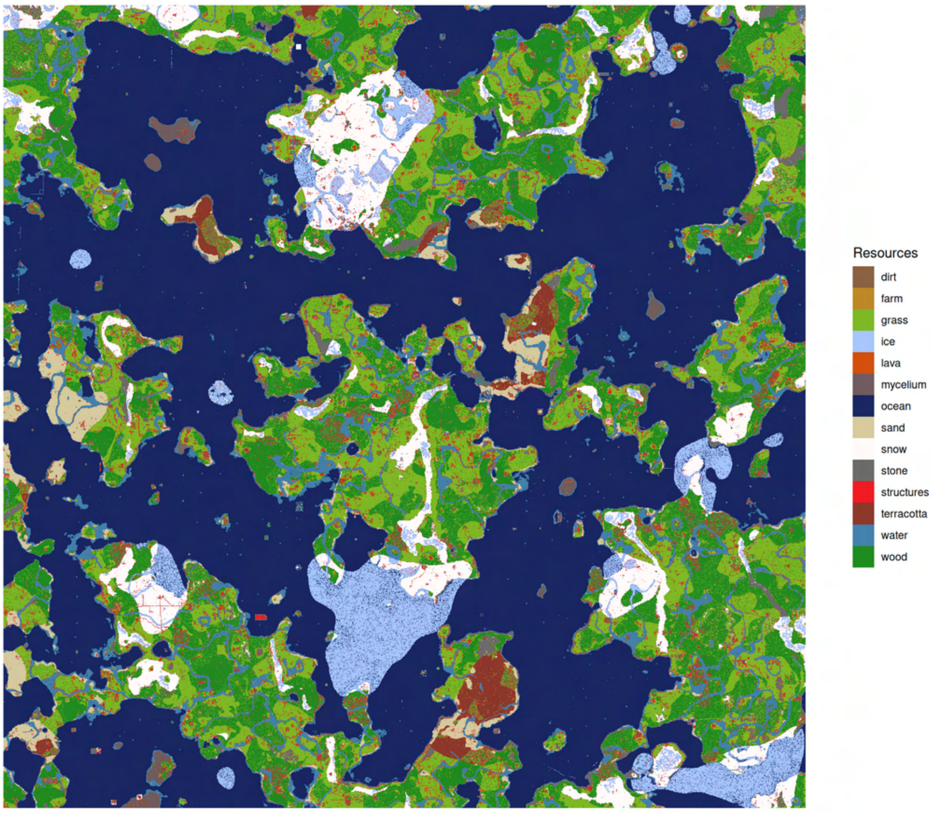

Figure A5: Map of Stoneworks Minecraft's current iteration's resource distribution as of April 2024.

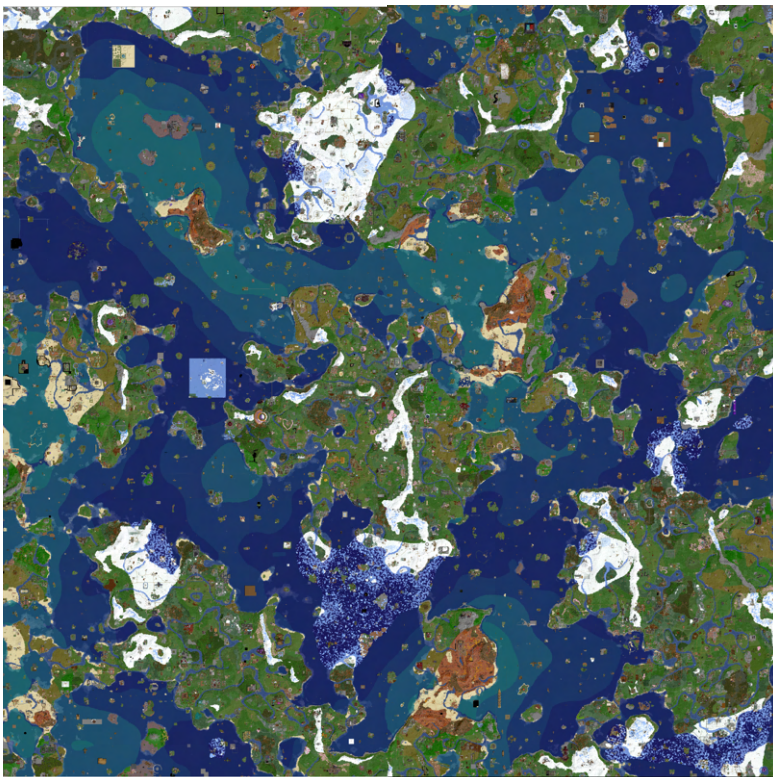

Figure A6: Map of Stoneworks Minecraft's current iteration as of February 2025, *Abexilas*.

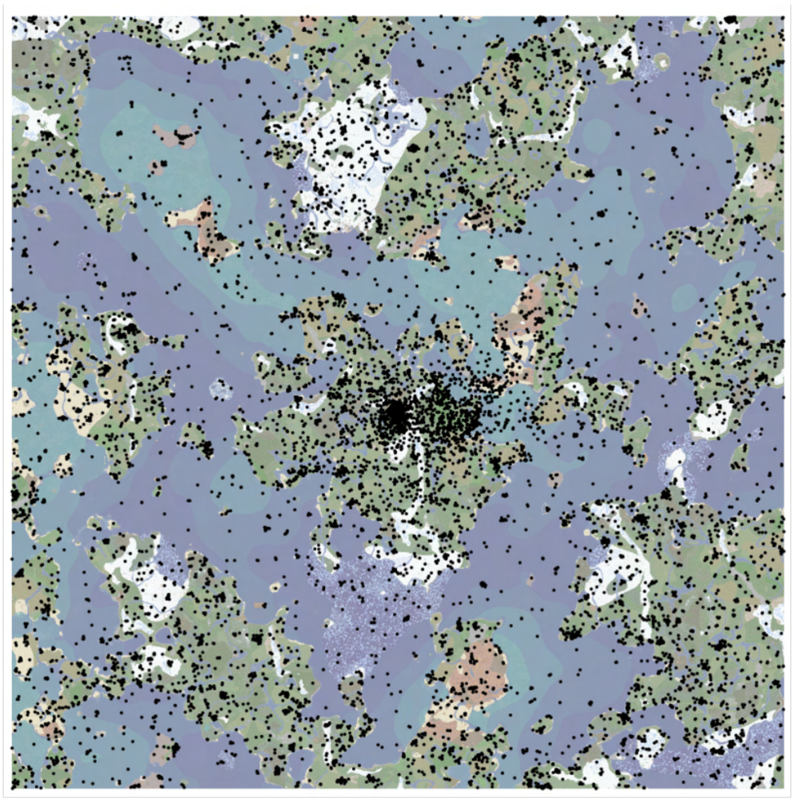

Figure A7: Map of Stoneworks Minecraft's current iteration as of April 2024, *Abexilas* with all starting locations.

randomly assigned starting location (1 variable). (transformed into inverse hyperbolic sine in regressions)

- **Lagged average share of sales (purchases) in food items of players surrounding a randomly assigned starting location (2 variables).**
- **Lagged average number of non-food items picked up, crafted, or purchased of players surrounding a randomly assigned starting location (1 variable).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged average number of non-food items dropped, used as input, or sold of players surrounding a randomly assigned starting location (1 variables).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged average share of non-food items crafted in total number of non-food items picked up, crafted, or purchased of players surrounding a randomly assigned starting location (1 variables).**
- **Lagged average share of non-food items used as input in total num-**

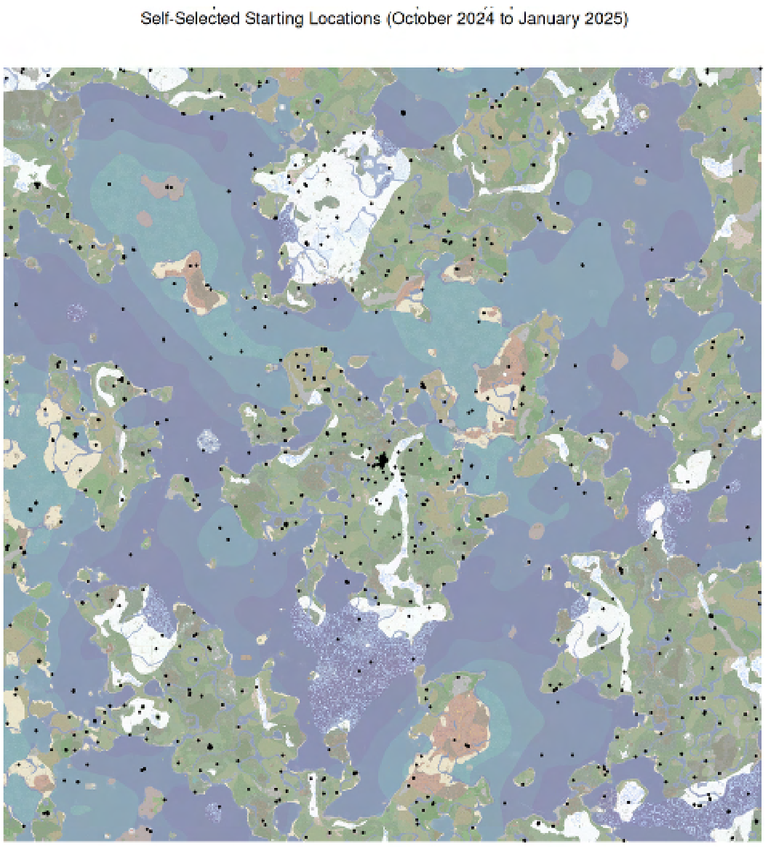

Figure A8: Map of Stoneworks Minecraft's current iteration as of April 2024, *Abexilas* with I_S starting locations.

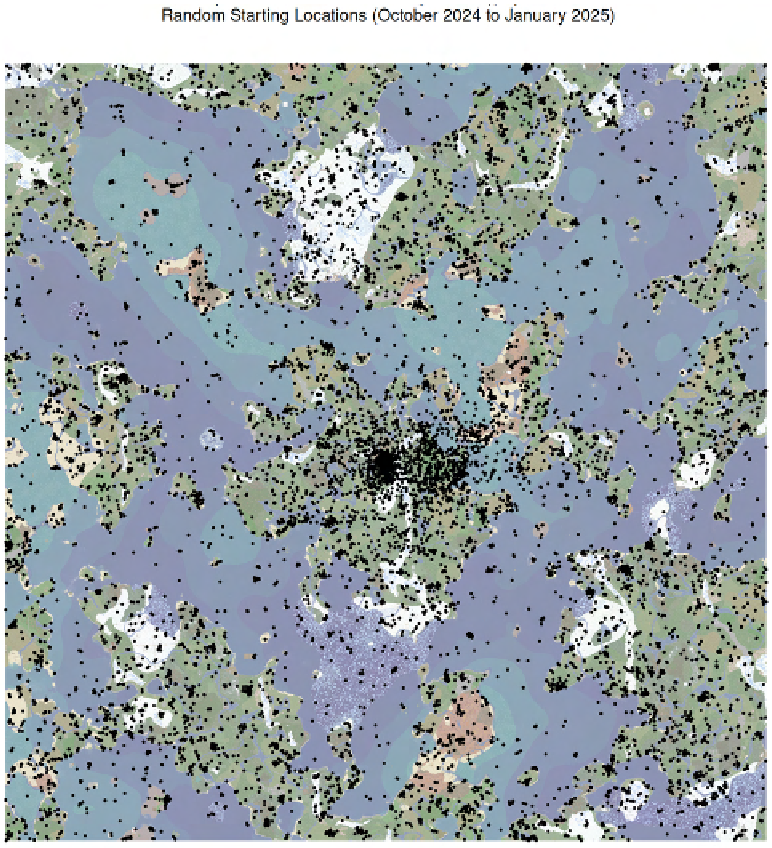

Figure A9: Map of Stoneworks Minecraft's current iteration as of April 2024, *Abexilas* with I_R starting locations.

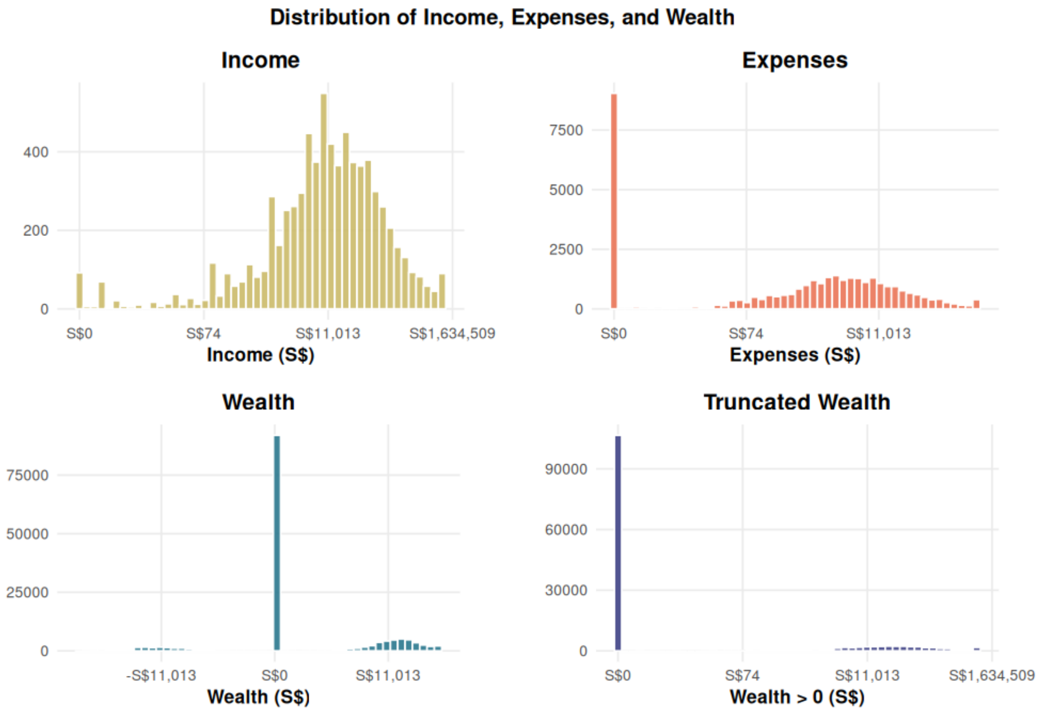

Figure A10: Histograms of user-period income, expenses, wealth, and wealth truncated at zero.

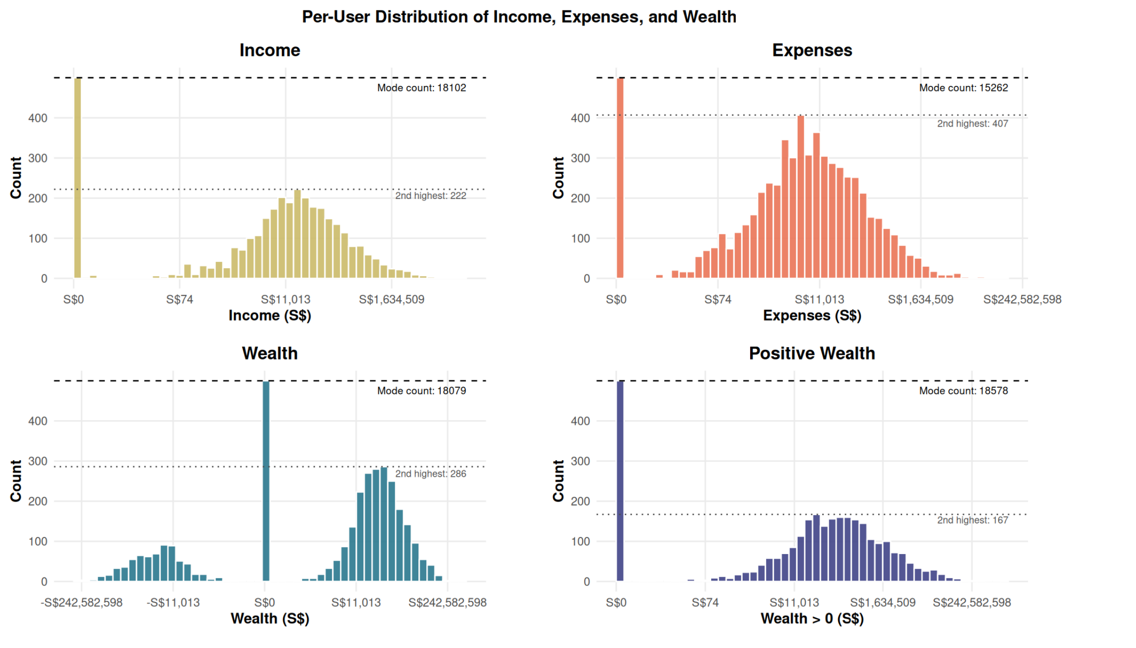

Figure A11: Histograms of cumulative user-level income, expenses, wealth, and wealth truncated at zero. The mode of the distribution (labeled in long dashed line) is not drawn at scale in order to make the rest of the histogram visible.

ber of non-food items dropped, used as input, or sold of players surrounding a randomly assigned starting location (1 variables).

- Lagged disaggregated average share of food pickups, food crafted, food used as input, food dropped, food purchased, and food sold in all category combinations of capital-intensive, appropriable, renewable, and land dependent foods of players surrounding a randomly assigned starting location ($6 \times 2 \times 2 \times 2 = 48$ variables).

- Lagged average share of food gain (in nutritional value) crafted, purchased, or picked up of players surrounding a randomly assigned starting location (3 variables).

- Lagged average share of food used (in nutritional value) used as input, sold, or dropped of players surrounding a randomly assigned starting location (3 variables).

- Lagged share of randomly assigned players surrounding a randomly assigned starting location (1 variable).

- Lagged share of players which stayed in their starting location ball

Figure A12: Histograms of user-period income, expenses, wealth, and wealth truncated at zero pooled over all periods, with y-axis scaled to inverse hyperbolic sine.

Figure A13: Histograms of the user averages of income, expenses, wealth, and wealth truncated at zero pooled over all periods, with y-axis scaled to inverse hyperbolic sine.

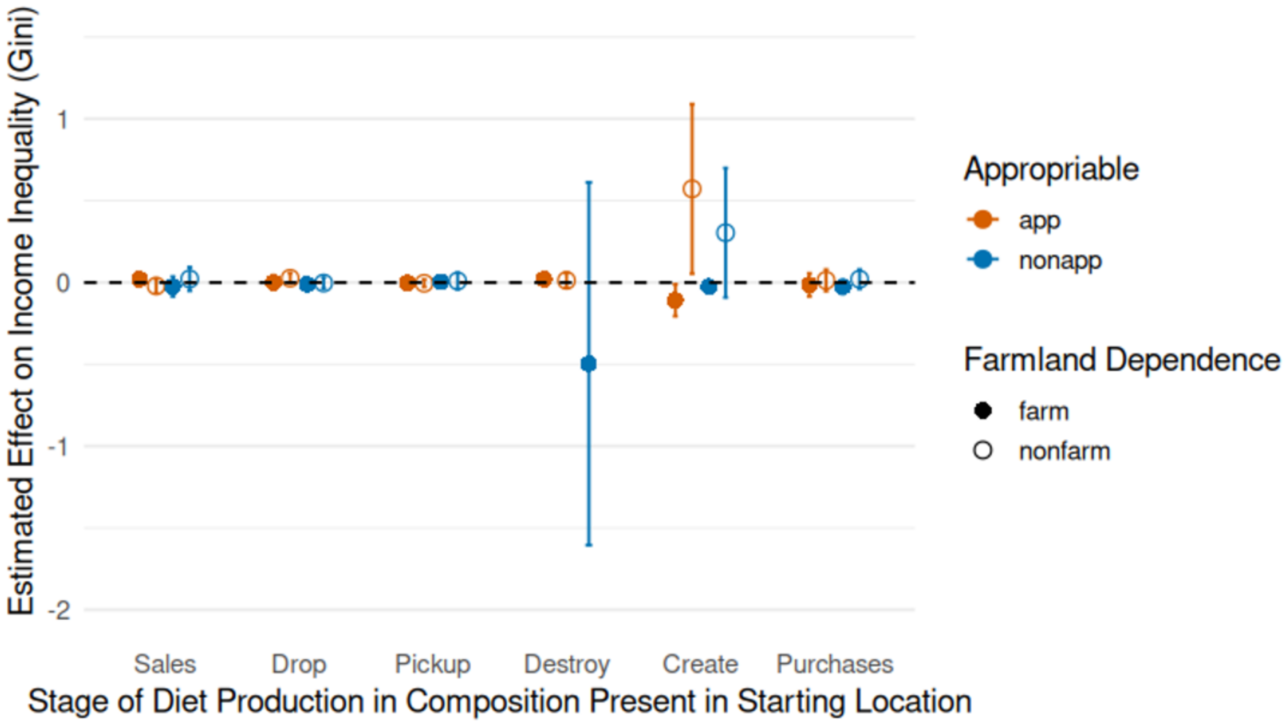

Figure A14: Coefficient estimates of decomposed food categories on income Gini.

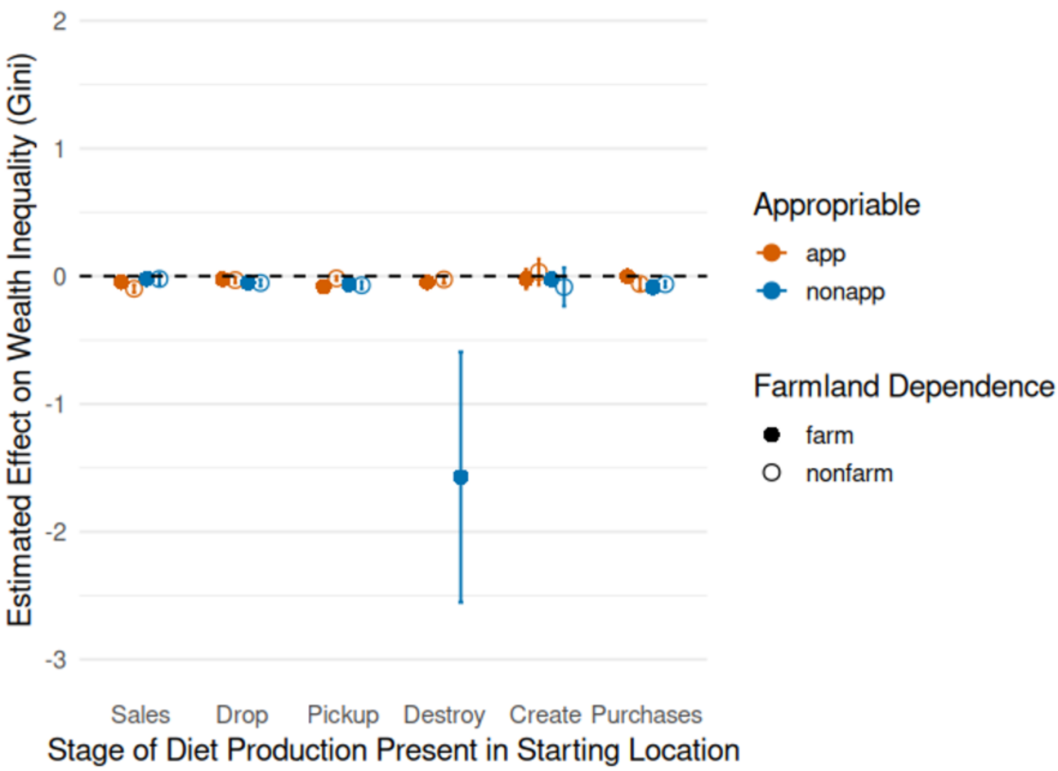

Figure A15: Coefficient estimates of decomposed food categories on wealth Gini.

surrounding a randomly assigned starting location (1 variable).

- **Lagged average tenure of players surrounding a randomly assigned starting location (1 variable).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged average playtime of players surrounding a randomly assigned starting location (1 variable).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged median transfer payments received (made) of players surrounding a randomly assigned starting location (2 variables).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged average level of income, expenses, and wealth of players surrounding a randomly assigned starting location (3 variables).** (transformed into inverse hyperbolic sine in regressions)
- **Lagged average within-group Gini coefficient of income and wealth of players surrounding a randomly assigned starting location (2 variables).**

D Random vs. Selected Players

Figure A7, A8, and A9 in the Appendix show the starting location coordinates of players in I_R and I_S both separately and together. By construction, the starting locations for players in I_S are more clustered than the starting locations for players in I_R.

I report a summary of the differences in variables, after controlling for cohort fixed effects, between players in I_R and I_S in Table A5 in the Appendix.[27] There is roughly a one-to-one ratio between the number of players in I_R and those in I_S in the study period, with some few but notable differences between the two groups.[28] I_R players have significantly higher income levels, have a greater share of their commands in land management and nation management, make more land claims, and are more likely to receive lands from other players. They pickup, drop, craft, and use more items, but they also pickup and craft less food. If one assumes that players are better off with a higher expected income, it would seem that I_R players are doing better than I_S players. However, the income variance for I_R players is much greater than that of I_S players (I_R s.e. = 12.45kS$, I_S s.e. = 4.66kS$), which suggests that one of the main benefits of being a self-selected player is variance reductions in exchange for lower expected income. This is consistent with the intuition that self-selected players might be more risk-averse than randomly assigned players; the same observation applies to wealth measures.

[27]Without adjusting for cohort fixed effects, all the differences are statistically significant at the 0.1% level.

[28]Without restricting to the study period, the ratio is closer to 13 to 28 (13,404 in I_R, 27,938 in I_S). However, the players outside the study period are missing their ChestShop locations as I mentioned in Section 3.2, which might suggest that the shop locations play a significant factor in properly identifying player groups.