

Urban Density and the Variety of Cultural Amenities: Evidence from Movie Theaters*

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Abstract

We study how urban density shapes movie variety. Movies are non-tradable amenities whose standardized nature enables precise measurement of local variety. Using granular box office data from Chinese cities, we document a density premium: denser neighborhoods offer more distinct films, genres, and foreign productions at similar prices. Exploiting COVID-19–induced population redistribution as a shock to localized density in an instrumented difference-in-differences framework, we find that a 10% increase in density raises the number of distinct movies by 0.6%, genres by 0.1%, and non-domestic films by 0.3%. Cultural variety responds endogenously to local demand, implying that policies affecting residential distribution shape cultural opportunities.

Keywords: Agglomeration, Cultural Amenity, Movie Theaters, Population Density

JEL classifications: D62, R12, R23, Z11.

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1 Introduction

Movie theaters are a major cultural amenity in modern urban life. As experience goods, films cater to a wide spectrum of heterogeneous tastes (Atkin, 2016; Davis et al., 2019; Couture et al., 2024, 2025), and the cultural narratives they convey are deeply intertwined with how individuals understand themselves and the world (Riley, 2024; Jia and Strömberg, 2025; Michalopoulos and Rauh, 2025). Because preferences over movies are heterogeneous, the *variety* of films available in a given location, not just their quantity, is a key determinant of consumer welfare. Yet not all neighborhoods offer the same breadth of cinematic choice. This paper examines whether urban density causally determines the variety of movies available to local audiences and through which margins (prices, quantities, or the range of content) this effect operates.

A large literature documents that denser markets support a wider array of consumption options, from tradable goods (Handbury and Weinstein, 2015) to non-tradable services such as restaurants (Schiff, 2015; Couture, 2016; Leonardi and Moretti, 2023). Yet establishing a causal link from density to service variety has proved difficult, in part because heterogeneity in quality and categorization complicates measurement in the non-tradable sector. Movie theaters offer a particularly clean setting to address this challenge. As place-bound venues, theaters are inherently local amenities whose offerings are tied to the neighborhoods they serve. At the same time, each film is a distinct, globally distributed product, analogous to a barcode-level item in Handbury and Weinstein (2015), enabling precise quantification of local variety while holding product quality constant across locations.

We study this question using detailed box office data from China, the world’s second-largest movie market.¹ The Chinese setting offers a key data advantage: we observe product-level information on prices, quantities, and title availability at fine spatial scales. To our knowledge, such data are uniquely available in this context. Using data from 2017 to 2019, we document a pronounced “density premium” in movie variety at a fine grid level (800 m × 800 m): denser neighborhoods offer significantly more distinct titles, genres,

¹Source: <https://www.bbc.com/news/business-21891631>.

and foreign films, despite nearly identical ticket prices across the density distribution.

Identifying the causal effect of density on movie variety faces two challenges. First, omitted variables jointly shape both population density and movie provision (Guerrini et al., 2013; Diamond, 2016; Lee and Lin, 2018; Borraz et al., 2024; Almagro and Domínguez-Iino, 2025). For example, dense neighborhoods tend to have more amenities that complement cinema attendance, such as restaurants and nightlife, which could inflate the estimated effect of density. At the same time, these neighborhoods may also offer substitutes, such as live entertainment, which could attenuate the estimated effect. The direction of bias is therefore theoretically ambiguous. The second identification challenge is reverse causality: neighborhoods with richer cultural offerings may attract residents, making movie variety a cause rather than a consequence of higher density and biasing estimates upward. Addressing these challenges requires a setting in which shifts in density are plausibly unrelated to local amenity conditions.

We exploit the COVID-19 pandemic as a source of such variation. The pandemic heightened health risks in crowded areas and sharply reduced commuting needs, inducing many households to relocate from dense urban cores to lower-density peripheral areas (Gupta et al., 2022; Coven et al., 2023; Huang et al., 2023; Ramani et al., 2024). Crucially, these relocations were driven by health and remote-work considerations rather than by local cultural amenity conditions, providing plausibly exogenous within-city variation in population density. Using high-resolution gridded population data, we confirm that initially denser areas experienced significant population outflows after 2020 and incorporate this population redistribution as the first stage of an instrumented difference-in-differences (DiD) framework.

In the reduced-form regressions, we find that the initial-density gradient in movie outcomes declined significantly after COVID-19: areas that were denser before the pandemic experienced disproportionately larger losses in variety. A 10% higher initial population density is associated with a 2.5% decline in population after COVID-19. Rescaling by this first-stage relationship, our instrumented DiD estimates indicate that a 10% increase in contemporaneous population density raises the number of distinct movies by about

0.6%, genres by 0.1%, non-domestic films by 0.3%, and movies with preview screenings by more than 1%. Ticket prices, by contrast, remain economically unchanged, confirming that the density premium operates through the breadth of available content rather than pricing. These adjustments unfold gradually rather than instantaneously, consistent with supply-side frictions in amenity provision and mirroring the lagged re-clustering of restaurants documented by [Leonardi and Moretti \(2023\)](#).

We assess potential threats to exclusion restrictions and provide evidence that the pandemic primarily affected cinema outcomes through changes in local population density. First, lockdown and mobility-restriction policies may have been more stringent in denser areas, potentially confounding our estimates. Re-estimating our main specifications after excluding the lockdown years (2020–2022) yields similar results, suggesting that differential policy stringency is unlikely to drive our findings. Second, changes in cinema activity could reflect behavioral responses rather than population shifts. For example, residents in denser neighborhoods may have been more reluctant to visit cinemas or more likely to substitute toward online streaming after COVID-19. Using mobile phone data from a major Chinese city, we show that residents in initially denser areas did not reduce their per-capita cinema visits and exhibited less substitution toward online consumption than residents in less dense areas. This evidence indicates that behavioral responses are unlikely to explain our baseline results.

Our findings contribute to the literature on agglomeration spillovers through endogenous amenities ([Ahlfeldt et al., 2015](#); [Schiff, 2015](#); [Couture, 2016](#); [Leonardi and Moretti, 2023](#)) and to the related literature on spatial variation in consumption variety and welfare ([Handbury and Weinstein, 2015](#); [Couture, 2016](#); [Handbury, 2021](#); [Borraz et al., 2024](#); [Almagro and Domínguez-Iino, 2025](#)). While prior studies focus primarily on restaurants or composite amenity indices and on variation across cities ([Berry and Waldfogel, 2010](#); [Schiff, 2015](#)), we examine how within-city differences in residential density shape the variety of a specific non-tradable service. By leveraging exogenous within-city population redistribution, we provide direct causal evidence that localized demand conditions determine not only the presence of amenities but also the variety of options they offer.

Our paper also complements the economics of movies literature, which has focused on box office revenue determinants (Moretti, 2011), cultural narratives (Michalopoulos and Rauh, 2025), environmental shocks (He et al., 2022; Xi et al., 2023), and spatial competition among cinemas (Chisholm et al., 2010; Chisholm and Norman, 2012; Elizalde, 2013; Takahashi, 2015). We instead treat movie theaters as components of a city’s amenity landscape, focusing on how their offerings respond endogenously to shifts in residential density.

2 Data and Motivating Evidence

2.1 Data

Our empirical analysis combines georeferenced movie consumption data with high-resolution population data at the grid-year level. The movie data come from the China Movie Database, an administrative source covering all theaters in Chinese cities from 2017 to 2023. The dataset reports daily theater-level box office revenue, ticket sales, and screenings, along with movie-level details such as titles, countries of production, and pre-view release status. We also match each movie to its corresponding entry on Douban, China’s counterpart to IMDb, which provides detailed genre classifications. The raw movie dataset contains 15,996 theaters and 6,451 unique movies.

Population data are drawn from the LandScan database, which estimates nighttime residential populations in grids of approximately $0.008^\circ \times 0.008^\circ$ (about $800\text{ m} \times 800\text{ m}$). For each grid, LandScan reports lower and upper population bounds; we use the midpoint in our main analysis, and the results are robust to using either bound. We measure population density in 2016, the year preceding our movie outcomes. We then use annual data from 2017 to 2023 to track changes. To our knowledge, LandScan offers the most fine-grained population estimates currently available. After geocoding theaters and merging the two datasets, the final sample includes 15,961 theaters located in 12,975 grids that contain at least one theater during 2017–2023. The data span more than 330 cities across China and cover 99% of the population and GDP.

We aggregate all movie outcomes to the grid-year level by summing across theaters within each grid cell. Specifically, box office revenue, ticket sales, and screenings are summed over all theaters in a grid in a given year, and the average ticket price is computed as total revenue divided by total tickets sold. To capture movie variety, we consider the number of distinct movies screened in a grid, the number of days a movie remains on screen, and the average number of screenings per movie, where the latter two capture temporal variety, or consumers’ flexibility in choosing when to watch. For genre exposure, we construct analogous measures: the number of distinct genres and the average number of screenings per genre. We also track the number of movies with preview screenings. Finally, we measure the number of non-domestic movies, which represent access to foreign cultural content that differs from domestic productions. Table [A1](#) presents summary statistics for the variables used in the analysis.

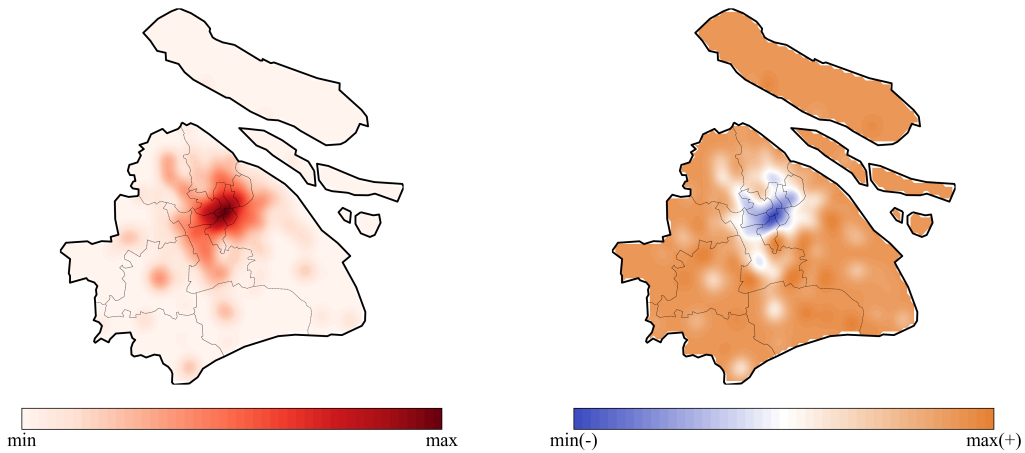
Our analysis further draws on mobile phone data from China Unicom, one of China’s major telecommunications operators. The data consist of two cross-sectional snapshots from November 2019 and November 2024, covering approximately 6.53 million users in Shanghai. We use these data to examine whether post-pandemic changes in theater visits and video streaming usage vary across neighborhoods with different population densities. We focus on the three leading Chinese streaming platforms, Tencent Video, iQIYI, and Youku, which together accounted for approximately 63% of the market in 2024. All variables from the mobile phone data are aggregated at the geohash-7 level (approximately $150 \text{ m} \times 150 \text{ m}$).

2.2 Motivating Evidence

Figure [A1](#) provides an overview of the Chinese movie market. China is the world’s second-largest movie market, with national box office revenue reaching 64 billion CNY (approximately US\$9.2 billion) and total ticket sales exceeding 1.7 billion in 2019 alone. Even after the disruptions caused by COVID-19, the market recovered to nearly 55 billion CNY and 1.3 billion tickets by 2023. The sheer scale of this market, combined with the granularity of available box office data, makes it a compelling setting in which to study

how density shapes local movie provision.

Movie availability in China, measured by the number of distinct movies screened, exhibits pronounced spatial heterogeneity. Figure 1 illustrates substantial within-city variation using Shanghai as an example. Panel (a) maps the pre-pandemic distribution (2017–2019) and shows a clear concentration of movie availability in the urban core, with substantially fewer titles in peripheral areas. This spatial pattern closely mirrors population density in Shanghai. Panel (b) shows that areas that have initial high-density and high movie availability experienced the sharpest declines in the number of available movies in the post-pandemic period (2020–2023) likely due to population losses. The panels suggest that the variety of movie provision likely responds to local demand at fine spatial scales and that shocks to density may reshape the geography of cultural amenity access within cities.



(a) Pre-Pandemic Movie Availability

(b) Change in Movie Availability

Figure 1: Movie Density and Post-Pandemic Changes in Shanghai

Notes: Panel (a) shows the average number of distinct movies screened per grid cell (approximately 800m \times 800m) in Shanghai during the pre-pandemic period (2017–2019). Panel (b) depicts the change in the average number of movies at each grid cell between the pre-pandemic period (2017–2019) and the post-pandemic period (2020–2023). Movie data are from the China Movie Database. Both panels are based on gridded data smoothed using Gaussian filters. In Panel (b), the color scale ranges from blue, indicating declines in the number of movies, to orange, indicating increases.

Using pre-COVID-19 data from 2017 to 2019, we document that densely populated

areas not only consume more movies but also exhibit broader and more diverse movie variety, a pattern we refer to as the “density premium of movie variety.” Figure A2 presents unconditional binned scatter plots of log movie outcomes against log population density in 2016, pooling grid-year observations over 2017–2019. Several patterns stand out. First, ticket prices are essentially flat across the density distribution (an elasticity of approximately -0.002), indicating that the density premium does not operate through pricing. Second, ticket sales and revenues increase steeply with density (elasticities of roughly 0.16 – 0.21), reflecting a strong demand-side scale effect. Third, and most relevant for our analysis, density is positively associated with every dimension of movie variety, including the number of distinct movies, genres, non-domestic films, preview screenings, days on screen, and screenings per movie and per genre. These variety elasticities range from approximately 0.006 for genres to 0.10 for screenings per genre, indicating that the density premium in variety extends well beyond the mechanical effect of having more theaters showing the same movies.

In summary, denser neighborhoods systematically enjoy richer cinematic offerings along multiple dimensions, while ticket prices remain nearly uniform across the density distribution. These cross-sectional patterns, however, do not establish causality: omitted variables may affect both density and movie markets, with theoretically ambiguous bias, and reverse causality from movie variety to residential sorting (Diamond, 2016; Couture et al., 2024; Almagro and Domínguez-Iino, 2025; Leonardi and Moretti, 2023) may further confound the relationship. We now turn to our empirical design, which exploits the COVID-19 pandemic as a source of plausibly exogenous variation in local population density.

3 Empirical Design

To isolate the causal effect of density on movie provision, we exploit COVID-19 as a natural experiment. The pandemic dramatically reshaped where people live and work by raising health risks in dense areas (Coven et al., 2023) and accelerating the adop-

tion of remote and hybrid work (Ramani et al., 2024). To the extent that COVID-19 affects local movie outcomes primarily through pandemic-induced population relocation, variation in pandemic exposure can serve as an instrument for shifts in neighborhood density. Intuitively, the pandemic induced larger population outflows from initially denser locations, generating exogenous variation in contemporaneous population density across neighborhoods that we exploit for identification.

Our identification strategy proceeds in three steps. First, we establish that COVID-19 induced a significant redistribution of population away from initially denser locations, which constitutes the *first stage* of our instrumental-variable strategy. Second, we present *reduced-form* DiD estimates that document how the gradient in movie outcomes with respect to initial density changed after the onset of COVID-19. Third, we complement these with *instrumental-variable* (IV) estimates, following the instrumented DiD framework of Hudson et al. (2017), to isolate the causal effect of contemporaneous population density on movie outcomes. We describe each step in turn, together with the identifying assumptions required for a causal interpretation and the evidence we marshal to assess their validity.

3.1 First Stage: COVID-19 and Population Redistribution

To quantify the pandemic-induced population redistribution, we estimate the following difference-in-differences specification:

$$Y_{lt} = \alpha + \beta \text{Density}_l \times \mathbb{1}(\text{After}_t) + \eta_l + \theta_t + \varepsilon_{lt}, \quad (1)$$

where Y_{lt} represents outcomes in logarithmic terms for grid l in year t , Density_l denotes log population density in 2016, and $\mathbb{1}(\text{After}_t)$ equals one for $t \geq 2020$ and zero otherwise. We include grid fixed effects, η_l , and year fixed effects, θ_t , and cluster standard errors at the grid level. When Y_{lt} is log contemporaneous population density, the coefficient β captures the differential change in population after 2020 associated with higher initial density, which constitutes the first-stage relationship.

Identifying assumption and assessment. The coefficient β has a causal interpretation under a *common trends* condition: absent COVID-19, locations with different 2016 density levels would have followed the same population trend. Because the treatment is continuous, we rely on the strong parallel trends assumption of Callaway et al. (2024).² While this assumption cannot be directly tested, in Section 4.1, we present event-study evidence showing that the pre-2020 coefficients are not significantly different from zero, and we further assess robustness using the pre-trend sensitivity analysis of Roth (2022) in Section 4.4.

3.2 Reduced Form: Initial-Density Gradient after COVID-19

The same specification in Equation (1) applies to the reduced-form regression, with Y_{it} now representing movie-related outcomes in logarithmic terms. The coefficient β captures the differential change in movie outcomes after 2020 associated with higher initial density. A negative estimate of β implies that more densely populated locations experienced larger declines in movie consumption or variety following the onset of COVID-19 relative to less densely populated locations.

Identifying assumption and assessment. The identification of the reduced-form coefficient relies on the same common trends condition as in the first stage, applied separately to each outcome. In Section 4.4, event-study evidence shows that the pre-2020 coefficients are not significantly different from zero across all outcomes, and we further assess robustness based on Roth (2022).

3.3 Instrumental Variables

While the reduced-form estimates document the total effect of initial density interacted with the pandemic, they reflect a composite of population shifts and other pandemic-related effects correlated with density. For example, cinemas in denser areas may have

²The strong parallel trends assumption outlined by Callaway et al. (2024) requires that, at each point of the density distribution, the observed paths of outcomes reflect the average counterfactual path that other locations would have experienced had they been at that same point of the density distribution. Strong parallel trends is likely a stronger assumption than the standard parallel trends required in DiD applications with binary treatment.

faced stricter lockdowns or capacity restrictions during the pandemic, which could directly affect movie outcomes independently of population changes. To isolate the causal effect of contemporaneous population density on movie outcomes, we use the interaction $Density_l \times \mathbb{1}(After_t)$ as an instrument for log contemporaneous population density. The IV model is given by the following first- and second-stage equations:

$$Density_{lt} = \phi Density_l \times \mathbb{1}(After_t) + \gamma_l + \delta_t + \nu_{lt}, \quad (2)$$

$$Y_{lt} = \omega \widehat{Density}_{lt} + \eta_l + \theta_t + \epsilon_{lt}, \quad (3)$$

where $Density_{lt}$ is log contemporaneous population density in grid l and year t , and γ_l and δ_t (and η_l and θ_t in Equation 3) denote grid and year fixed effects, respectively. The IV parameter ω equals the ratio of the reduced-form coefficient to the first-stage coefficient and measures the causal effect of population density on movie outcomes.

Identifying assumptions. A causal interpretation of the IV parameter ω in Equation (3) requires two conditions beyond the exogeneity of the instrument discussed in Section 3.1. First, the instrument must be *excludable* from the second stage: conditional on grid and year fixed effects, pre-sample population density interacted with the post-pandemic indicator must affect movie outcomes *only through* its impact on contemporaneous population, and not through any other channel. Second, we require *monotonicity*: higher initial density must make it weakly more likely that a grid experiences a population decline after COVID-19, so that there are no “defiers” whose population moves in the opposite direction of the instrument (Imbens and Angrist, 1994). Under these assumptions, together with a relevant first stage, the IV estimate can be interpreted as the local average treatment effect (LATE) for locations whose contemporaneous population was shifted by the pandemic-induced redistribution.

Assessing the assumptions. The first-stage results, reported in Section 4.1, yield F-statistics well above conventional thresholds (Tables A4 and A5), establishing instrument relevance. Section 4.5 provides suggestive evidence supporting the monotonicity condition. As for the exclusion restriction, it may be violated if, for example, the pandemic

directly affected cinema supply through lockdown policies or capacity restrictions that were more stringent in denser areas, or if COVID-19 triggered compositional changes in the local population (e.g., more movie-prone residents) that affect movie outcomes independently of population size. Although the exclusion restriction cannot be tested directly, Section 5 presents evidence against these alternative channels.

4 Results

We now present results corresponding to the three steps of our identification strategy: first-stage population redistribution, reduced-form effects on movie outcomes, and instrumental-variable estimates.

4.1 First Stage: COVID-19 and Population Redistribution

We begin by establishing that the COVID-19 pandemic induced a significant redistribution of population away from dense urban cores. Panel A of Table 1 shows the estimates from Equation (1) when the outcome is contemporaneous log population density. Before the pandemic, population patterns displayed strong persistence. As shown in Column 1, denser locations in 2016 continued to host larger populations in subsequent years: a 10% higher initial density translated into a 9.4% higher population before 2019, a clear sign of path dependence. Yet this trajectory shifted dramatically after 2020. Column 2 reveals that a 10% higher initial density is associated with approximately a 2.5% larger decline in population density after the pandemic, consistent with pandemic-related decentralization documented in the broader literature (Ramani et al., 2024).

Panel A of Figure 2 visualizes these dynamics using the event-study specification in Equation (4). Prior to 2020, population density exhibits a modest downward pre-trend in initially denser locations. However, after the onset of COVID-19, we observe a steep and sustained decline in population in previously higher-density areas. The sharp break in 2020 suggests that the population losses were a direct response to the pandemic rather

Table 1: Changes in Population Density and Initial-Density Gradients for Movie Consumption

	(1)	(2)
<i>Panel A. Population</i>		
log(pop)	0.9441*** (0.0024)	
After × log(pop)	-0.2486*** (0.0039)	-0.2485*** (0.0039)
Adjusted R-squared	0.837	0.911
Obs.	90,376	90,376
<i>Panel B. Tickets</i>		
log(pop)	0.1636*** (0.0064)	
After × log(pop)	-0.0254*** (0.0049)	-0.0457*** (0.0038)
Adjusted R-squared	0.285	0.800
Obs.	69,955	69,205
<i>Panel C. Revenue</i>		
log(pop)	0.1618*** (0.0065)	
After × log(pop)	-0.0247*** (0.0050)	-0.0459*** (0.0040)
Adjusted R-squared	0.278	0.796
Obs.	69,972	69,222
<i>Panel D. Price</i>		
log(pop)	-0.0021*** (0.0005)	
After × log(pop)	0.0006 (0.0005)	-0.0003 (0.0004)
Adjusted R-squared	0.387	0.723
Obs.	69,955	69,205
Year FE	Yes	Yes
City FE	Yes	No
Grid FE	No	Yes

Notes: This table reports difference-in-differences estimates of changes in the initial-density gradient after COVID-19, using grid-level data (approximately 800m × 800m) from 2017 to 2023. Each regression regresses log outcomes on the interaction of log population density (measured in 2016) and a post-2020 indicator, controlling for fixed effects. Panel A: log population; Panel B: log ticket sales; Panel C: log box office revenue; Panel D: log average ticket price. Column (1) includes year and city fixed effects; Column (2) includes year and grid fixed effects. Standard errors clustered at the grid level are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

than a continuation of a pre-existing trend.³

4.2 Reduced Form: Movie Consumption

Table 1 presents estimates of overall market activity, including ticket sales (Panel B), box office revenue (Panel C), and ticket prices (Panel D). Column (1) includes year and city fixed effects, whereas Column (2) includes year and grid fixed effects. Results from both specifications indicate that higher density was associated with greater consumption before COVID-19: a 10% increase in population density corresponded to a 1.6% increase in ticket sales and box office revenue, while ticket prices declined by only 0.02%, indicating virtually no meaningful change in prices. After the pandemic, however, this initial-density gradient weakened substantially. The effect of density on both ticket sales and revenue declined by about 0.5%, indicating that audiences in denser urban areas reduced attendance more sharply, even as theaters largely held prices constant.

Panels B through D of Figure 2 present the corresponding event-study estimates for ticket sales, box office revenue, and ticket prices. The pre-2020 coefficients for ticket sales and revenue are close to zero and not statistically significant, supporting the parallel trends assumption stated in Section 3.2. After 2020, both outcomes exhibit a clear downward shift, mirroring the population dynamics shown in Panel A. By contrast, the price panel shows no meaningful change, consistent with the interpretation that density operates on movie outcomes through quantities rather than prices.

4.3 Reduced Form: Movie Variety

We next turn to measures related to the variety of movie provision, summarized in Table 2, Panels A through G. Prior to COVID-19, density strongly predicted greater variety in movie offerings across all dimensions. A 10% increase in density was associated with more movies on screen, a greater number of non-domestic films, broader genre diversity, more preview screenings, longer screening durations, and more screenings per film and

³We further assess the sensitivity of this conclusion using the approach of Roth (2022) in Figure A3, which confirms that our estimated effects are unlikely to be driven by spurious pre-trends.

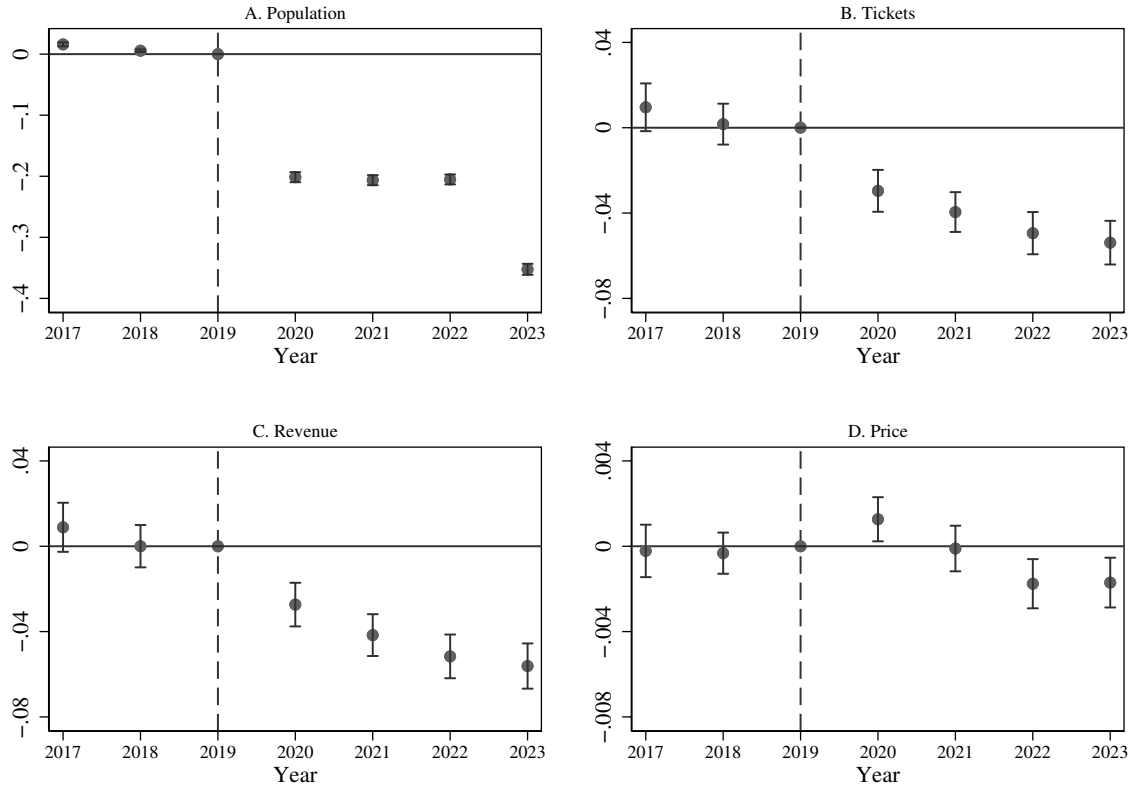


Figure 2: Changes in Population Density and Initial-Density Gradients for Movie Consumption

Notes: This figure plots year-specific coefficients and 95% confidence intervals from an event-study specification that interacts log population density (measured in 2016) with year dummies, controlling for grid and year fixed effects. The reference year is 2019. Panel A: log population; Panel B: log ticket sales; Panel C: log box office revenue; Panel D: log average ticket price. The sample covers grid-level data (approximately $800\text{m} \times 800\text{m}$) from 2017 to 2023.

per genre. After COVID-19, these initial-density gradients eroded consistently. The significant declines occur in the number of distinct movies, non-domestic films, and genres, which are extensive-margin measures that directly reflect the range of content available to local audiences. We also observe reductions in temporal variety, including days on screen, screenings per movie, and screenings per genre. The number of movies with preview screenings before their official release also declines.

Although the post-pandemic declines are individually modest in magnitude, ranging from 0.02% to 0.4% per 10% increase in initial density, they are remarkably consistent across all seven variety dimensions. This pervasive erosion of the initial-density gradient in variety is the paper’s central empirical finding: localized demand conditions, as proxied by residential density, are a key determinant of the breadth of cultural amenities available in a neighborhood. Tables 1 and 2 together indicate a systematic contraction in movie provision, with dense urban areas experiencing declines in both the volume and diversity of movie offerings following the pandemic.

4.4 Event-Study Evidence

We conduct an event study to assess the plausibility of the parallel trends assumption by examining whether outcomes in higher- and lower-density locations exhibit similar pre-treatment dynamics. The specification is as follows:

$$Y_{lt} = \alpha + \sum_{\tau \in T} \beta_{\tau} \text{Density}_{l} \times \mathbf{1}(t = \tau) + \eta_l + \theta_t + \varepsilon_{lt}, \quad (4)$$

where T is the set of years between 2017 and 2023, Density_{l} denotes log population density in 2016, and Y_{lt} represents movie-related outcomes in logarithmic terms. This specification is analogous to Equation (1) but replaces the single post indicator with year-specific dummies interacted with baseline density, allowing the effect of baseline density to vary flexibly over time. The coefficients β_{τ} therefore trace the differential evolution of Y_{lt} by initial density in each year τ relative to 2019.

Figure 2 reports the dynamic patterns for population and movie consumption out-

Table 2: Changes in Initial-Density Gradients for Varieties

	(1)	(2)
<i>Panel A. Movies</i>		
log(pop)	0.0331*** (0.0021)	
After × log(pop)	-0.0034 (0.0022)	-0.0144*** (0.0022)
Adjusted R-squared	0.199	0.445
Obs.	70,147	69,406
<i>Panel B. Days</i>		
log(pop)	0.0204*** (0.0014)	
After × log(pop)	0.0024* (0.0014)	-0.0042*** (0.0012)
Adjusted R-squared	0.294	0.624
Obs.	70,147	69,406
<i>Panel C. Screenings per movie</i>		
log(pop)	0.0612*** (0.0028)	
After × log(pop)	-0.0039* (0.0021)	-0.0088*** (0.0015)
Adjusted R-squared	0.232	0.844
Obs.	70,147	69,406
<i>Panel D. Genres</i>		
log(pop)	0.0056*** (0.0005)	
After × log(pop)	0.0008 (0.0006)	-0.0020*** (0.0007)
Adjusted R-squared	0.044	0.271
Obs.	70,144	69,403
<i>Panel E. Screenings per genre</i>		
log(pop)	0.0886*** (0.0039)	
After × log(pop)	-0.0082** (0.0032)	-0.0212*** (0.0027)
Adjusted R-squared	0.208	0.711
Obs.	70,144	69,403
<i>Panel F. Movies with preview screenings</i>		
log(pop)	0.0776*** (0.0034)	
After × log(pop)	-0.0323*** (0.0029)	-0.0362*** (0.0025)
Adjusted R-squared	0.291	0.649
Obs.	67,602	66,778
<i>Panel G. Non-domestic movies</i>		
log(pop)	0.0286*** (0.0019)	
After × log(pop)	0.0020 (0.0021)	-0.0068*** (0.0022)
Adjusted R-squared	0.289	0.500
Obs.	69,637	68,899
Year FE	Yes	Yes
City FE	Yes	No
Grid FE	No	Yes

Notes: This table reports difference-in-differences estimates of changes in the initial-density gradient for movie variety after COVID-19, using grid-level data (approximately 800m × 800m) from 2017 to 2023. Each regression regresses log outcomes on the interaction of log population density (measured in 2016) and a post-2020 indicator, controlling for fixed effects. Panel A: number of movies; Panel B: days on screen; Panel C: screenings per movie; Panel D: number of genres; Panel E: screenings per genre; Panel F: movies with preview screenings; Panel G: number of non-domestic movies. All dependent variables are in logs. Column (1) includes year and city fixed effects; Column (2) includes year and grid fixed effects. Standard errors clustered at the grid level are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

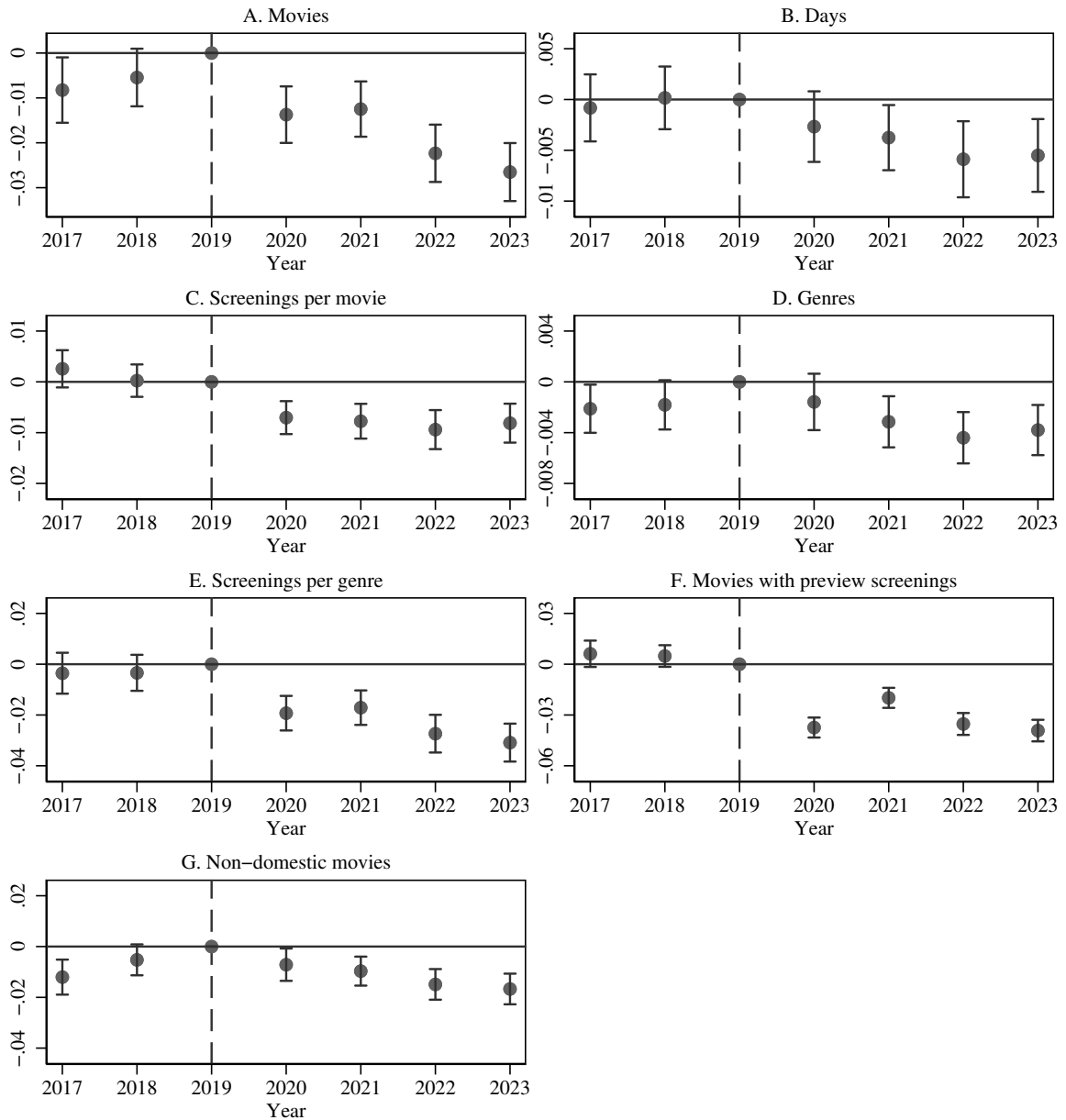


Figure 3: Temporal Changes in Initial-Density Gradients for Movie Varieties

Notes: This figure plots year-specific coefficients and 95% confidence intervals from an event-study specification that interacts log population density (measured in 2016) with year dummies, controlling for grid and year fixed effects. The reference year is 2019. The panels report results for movie variety outcomes: (A) number of movies, (B) number of non-domestic movies, (C) number of genres, (D) movies with preview screenings, (E) days on screen, (F) screenings per movie, and (G) screenings per genre. All dependent variables are in logs. The sample covers grid-level data (approximately $800m \times 800m$) from 2017 to 2023.

comes. Before COVID-19, the initial-density gradient for movie consumption was largely stable, as the pre-2020 coefficients are not statistically different from zero. Beginning in 2020, however, the initial-density gradient declines markedly across outcomes. These patterns are consistent with the interpretation that the declines documented in Tables 1 and 2 are driven by the onset of COVID-19 rather than by pre-existing differential trends. Notably, while population density drops abruptly in dense areas, movie consumption adjusts more gradually, suggesting lagged responses by both consumers and suppliers in reallocating urban demand.

Figure 3 reports the corresponding event-study estimates for movie variety outcomes. Before 2020, the coefficients are small and not statistically significant, further supporting the parallel trends assumption. Following the onset of COVID-19, variety measures exhibit a consistent downward shift, mirroring the broader market dynamics documented in Figure 2.

While event-study plots are useful for assessing the plausibility of the parallel trends assumption (Roth et al., 2023), Roth (2022) caution that tests for pre-trends may be underpowered to detect potential violations. To address concerns about noisy pre-trends, we follow their approach and augment our event-study plots by overlaying solid red lines that represent positive linear pre-trends detectable with 50% power (Figure A4) or 80% power (Figure A5). We also plot dashed blue lines showing the coefficients that would arise under these linear trends when no significant pre-trend is detected. In nearly all cases, the simulated lines fall outside the post-COVID confidence intervals, suggesting that our estimated treatment effects are unlikely to be driven by spurious pre-trends, even under conservative assumptions.

4.5 Instrumental-Variable Estimates

We complement the reduced-form estimates with two-stage least squares (2SLS) estimation using the IV model specified in Equations (2)–(3), as reported in Tables A4 and A5. The first-stage results yield F-statistics well above conventional thresholds, confirming instrument relevance. Intuitively, the Wald estimator rescales the reduced-form effects

by approximately $1/\phi \approx 4.02$, because the instrument induces relatively modest changes in contemporaneous population. Each unit of reduced-form effect on movie outcomes therefore corresponds to a larger causal effect of population density, as only a fraction of the variation in density is driven by pandemic-induced relocation.

Across most outcomes, the IV estimates are larger in absolute value than their OLS counterparts (Tables A2 and A3), indicating that OLS generally understates the effect of population density. For example, the 2SLS estimates exceed OLS for tickets, revenue, the number of distinct movies, genres, and movies with preview screenings. There are three notable exceptions. First, the estimated price effects are economically negligible in both specifications. Second, the estimates are nearly identical across methods for screenings per genre and non-domestic movies. Third, for some temporal measures, OLS estimates exceed IV estimates, including days on screen and screenings per movie.

Quantitatively, the IV estimates imply that a 10% increase in population density raises ticket sales and box office revenue by roughly 1.9%, while expanding the range of available content along multiple dimensions. The number of distinct movies increases by about 0.6%, genres by about 0.1%, and non-domestic films by about 0.3%. Movies with preview screenings also rise by more than 1%, indicating greater experimentation and pre-release exposure in denser markets. Intensive-margin measures such as days on screen and screenings per movie increase more modestly, on the order of 0.2 to 0.4%. In contrast, ticket prices change by less than 0.02%, remaining economically negligible. Overall, the evidence indicates that higher population density primarily expands market scale and variety, with virtually no effect on prices.

A LATE interpretation of these IV estimates requires the monotonicity condition discussed in Section 3.3. Table A6 provides suggestive evidence in support of this assumption by reporting the first-stage relationship separately for four quartiles of city-level average density. In each subgroup, the coefficient on the interaction of initial grid-level density with the post-COVID indicator is negative and highly significant, indicating that higher initial density is associated with larger population declines regardless of the overall density of the city. Figures A6 and A7 offer complementary evidence by grouping grids into

eight and four initial-density bins, respectively, and plotting the estimated post-COVID population change for each bin. In both cases, population declines increase approximately monotonically with initial density, consistent with the absence of defiers.

5 Threats to the Exclusion Restriction

While the exclusion restriction cannot be tested directly, we evaluate potential threats and provide evidence that the primary channel through which the pandemic affected cinema outcomes operates through changes in local population density.

5.1 Excluding Lockdown Periods

First, lockdown and mobility restriction policies may have been more stringent in denser areas, potentially confounding the estimated effects of density. However, any direct effects of such policies should have dissipated once nationwide restrictions were lifted at the end of 2022. Consistent with this interpretation, the year-specific estimates in Figure 3 show a persistent impact in 2023. Moreover, Tables A7 and A8 report estimates obtained after excluding the lockdown years 2020 to 2022, which remain qualitatively similar to the baseline results. Taken together, this evidence suggests that differential policy stringency is unlikely to drive our findings.

5.2 Cinema Visits and Online Substitution

Another key concern is that the observed decline in offline cultural consumption may reflect behavioral changes among residents who remain in place rather than population reallocation. For example, individuals may have developed a lower propensity to attend cinemas or substituted toward online consumption such as video streaming, particularly in denser neighborhoods. To distinguish between these mechanisms, we leverage mobile phone data from Shanghai in 2019 and 2024 (described in Section 2.1) that capture both physical mobility and online behavior, allowing us to compare changes in cinema visits and online consumption across neighborhoods with different population densities.

With the mobile phone data, we construct a grid cell by year panel and re-estimate Equation (1), where the outcome variable Y_{lt} captures either per capita cinema visits to grid cell l or nearby locations in year t , or per capita video usage measured by cellular data consumption or time spent, all in logarithms. Since outcomes are measured on a per capita basis, the coefficient β captures changes in individual behavior conditional on local population size. A negative estimate of β indicates a larger post-pandemic decline in per capita cinema visits in initially denser areas, while a positive estimate indicates a larger increase in per capita online consumption.

Table A9 presents the results for visits to cinemas. In all specifications, visits are restricted to non-home and non-work trips lasting at least 90 minutes and are normalized by the local population in each grid cell. Column 1 considers visits to grid cells that contained cinemas in 2019. Column 2 accounts for visits to grid cells with cinemas in the corresponding year, allowing the set of cinema locations to vary over time. Column 3 expands the definition to include visits to grid cells within 100 meters of cinemas in 2019, while Column 4 restricts visits to those lasting no more than 360 minutes. The sample is limited to grid cells with at least five residents in Panel A and at least ten residents in Panel B, in both 2019 and 2024. Across all specifications, the positive interaction coefficients indicate that residents in areas that were initially more densely populated did not curtail their visits to cinemas after the pandemic. Instead, visits tended to increase on a per-capita basis, suggesting that in-person cultural consumption remained resilient even as overall population levels declined.

Table A10 reports the corresponding results for online video consumption. In Columns 1 and 3, the dependent variable is the logarithm of monthly data usage per resident, whereas in Columns 2 and 4 it is the logarithm of monthly time spent on video apps. The sample is restricted to grid cells with at least five residents in Columns 1 and 2 and at least ten residents in Columns 3 and 4, in both years. The negative coefficients on the interaction term indicate that denser neighborhoods exhibited weaker substitution toward online consumption. These results suggest that the observed post-pandemic changes in cinema activity are unlikely to be driven by a shift toward online alternatives. In fact,

our estimates of the impact of population density on offline cultural consumption likely represent a conservative lower bound.

6 Conclusion

This paper addresses a central question: how does urban density shape the variety of movies, an important non-tradable cultural amenity? Using detailed box office data from Chinese cities, we show that denser neighborhoods systematically offer a wider range of films, including more distinct titles, genres, foreign productions, and preview screenings, while low-density areas face substantially more limited choice. Importantly, these differences arise despite nearly identical ticket prices across locations, suggesting that the density premium operates through the breadth of available content rather than through pricing. To establish causality, we exploit the COVID-19 pandemic as an exogenous shock to residential location choices within cities. Pandemic-induced population outflows from dense urban cores eroded the variety advantage of high-density neighborhoods across multiple dimensions, while areas gaining population saw expanded offerings. These adjustments unfolded gradually, consistent with supply-side frictions in cultural amenity provision.

Our findings highlight the endogenous nature of cultural amenity variety and its sensitivity to localized demand conditions. While existing research has documented that denser markets support a wider array of tradable goods ([Handbury and Weinstein, 2015](#)) and non-tradable services such as restaurants ([Schiff, 2015](#); [Couture, 2016](#); [Leonardi and Moretti, 2023](#)), the causal link from density to service variety has been difficult to isolate. By leveraging movies as precisely measurable “barcode-level” products and exploiting plausibly exogenous variation in local density, our analysis provides direct causal evidence for this channel. The results underscore that variety, defined as the range of options available to consumers, is a key margin through which density shapes the urban consumption landscape, with implications for welfare inequality across neighborhoods ([Handbury, 2021](#); [Couture et al., 2024](#)). More broadly, urban policies affecting residen-

tial distribution, whether through housing supply, transport infrastructure, or land use planning, indirectly shape the cultural variety available to residents.

Several limitations point to directions for future research. Our data do not allow us to disentangle the extensive margin of cinema entry and exit from the intensive margin of programming decisions by incumbent theaters. We document causal effects on variety but do not quantify the associated welfare implications; a structural framework incorporating heterogeneous preferences and endogenous theater location could address this gap. Finally, whether the density–variety relationship we document for movies extends to other cultural amenities, and how different amenities interact in shaping neighborhood attractiveness, are important questions for future work.

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Online Appendix [For Online Publication]

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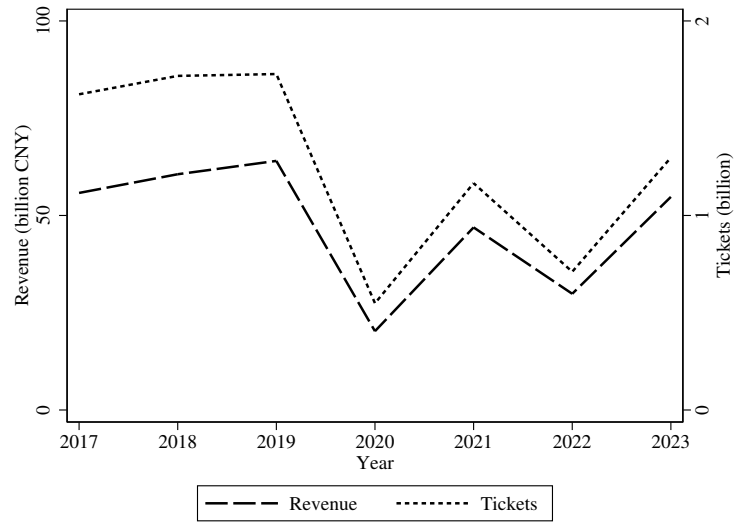


Figure A1: China's Box Office Revenue and Ticket Sales, 2013–2023

Notes: This figure shows national annual box office revenue (in billions of CNY) and ticket sales (in billions of admissions) in China from 2013 to 2023, using data from the China Movie Database.

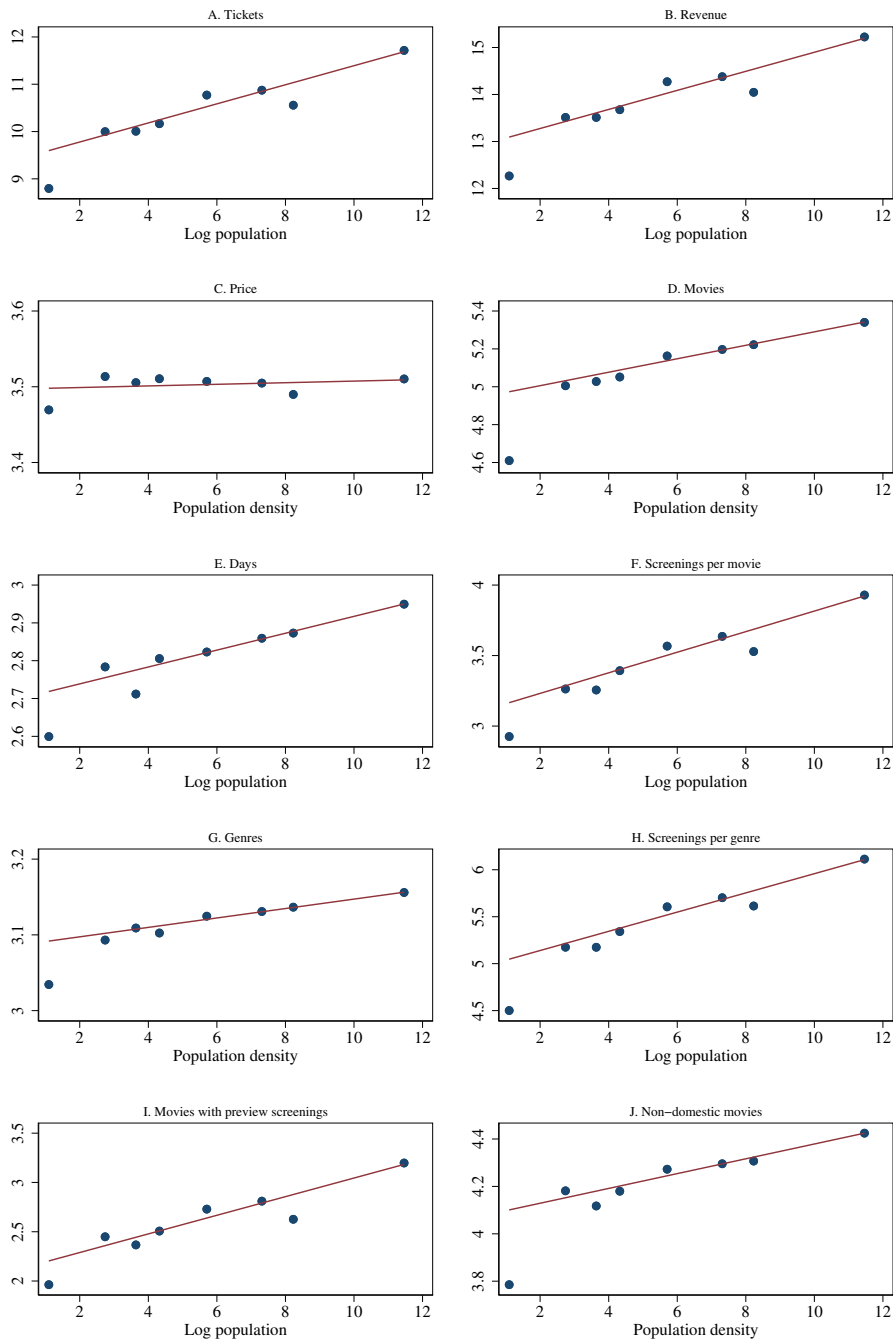


Figure A2: Cross-Sectional Relationship between Population Density and Movie Outcomes

Notes: This figure presents binned scatter plots of the relationship between population density and movie-market outcomes at the grid level ($800\text{m} \times 800\text{m}$). The x-axis reports log population density in 2016. The y-axes report outcomes in logs. Each dot represents the mean outcome within a bin of population density (using grid-year observations pooled over 2017–2019), and the solid line shows the corresponding linear fit: (A) number of tickets, (B) revenues, and (C) average movie ticket price, (D) number of movies, (E) average theatrical run (days), (F) screens per movie, (G) number of genres, (H) screens per genre, (I) movies with preview access, and (J) number of non-domestic films.

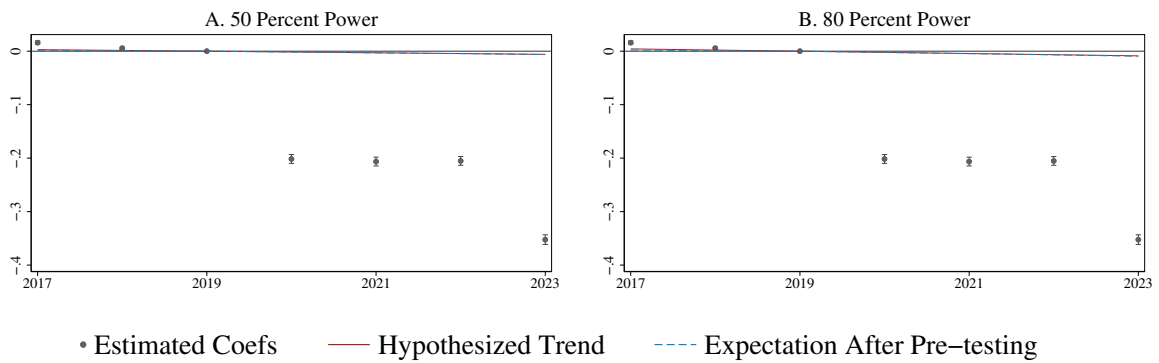


Figure A3: Pre-Trend Sensitivity Analysis, Population

Notes: This figure overlays pre-trend sensitivity analysis from Roth (2022) on the event-study estimates from Figure 1. The outcome variable is population density from 2017–2023, and the independent variable is baseline population density measured in 2016. The solid red lines show the positive linear pre-trend detectable with 50% power (Panel A) and 80% power (Panel B). The dashed blue lines show the post-treatment coefficients that would arise under this linear trend when no significant pre-trend is detected. In both panels, the simulated coefficients (dashed blue) fall outside the post-COVID confidence intervals, suggesting that estimated treatment effects are unlikely to be driven by spurious pre-trends. The reference year is 2019. All variables are in logs.

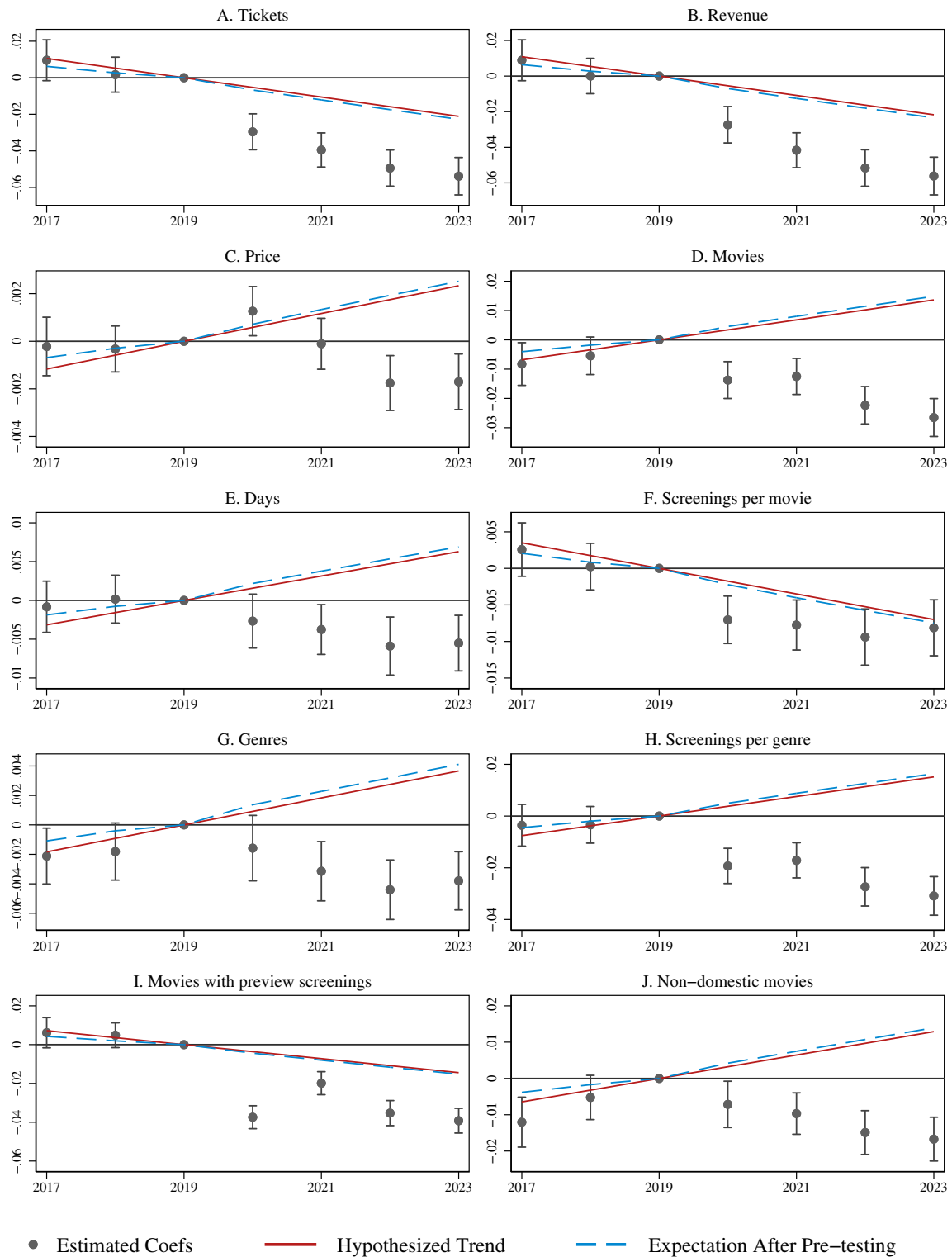


Figure A4: Pre-Trend Sensitivity Analysis, 50 Percent Power

Notes: This figure overlays pre-trend sensitivity analysis from Roth (2022) on the event-study estimates from Figures 2 and 3. Each panel corresponds to a different outcome variable. The solid red lines show the positive linear pre-trend detectable with 50 percent power. The dashed blue lines show the post-treatment coefficients that would arise under this linear trend when no significant pre-trend is detected. In nearly all panels, the simulated coefficients (dashed blue) fall outside the post-COVID confidence intervals, suggesting that estimated treatment effects are unlikely to be driven by spurious pre-trends. The reference year is 2019. All variables are in logs; population density is measured in 2016.

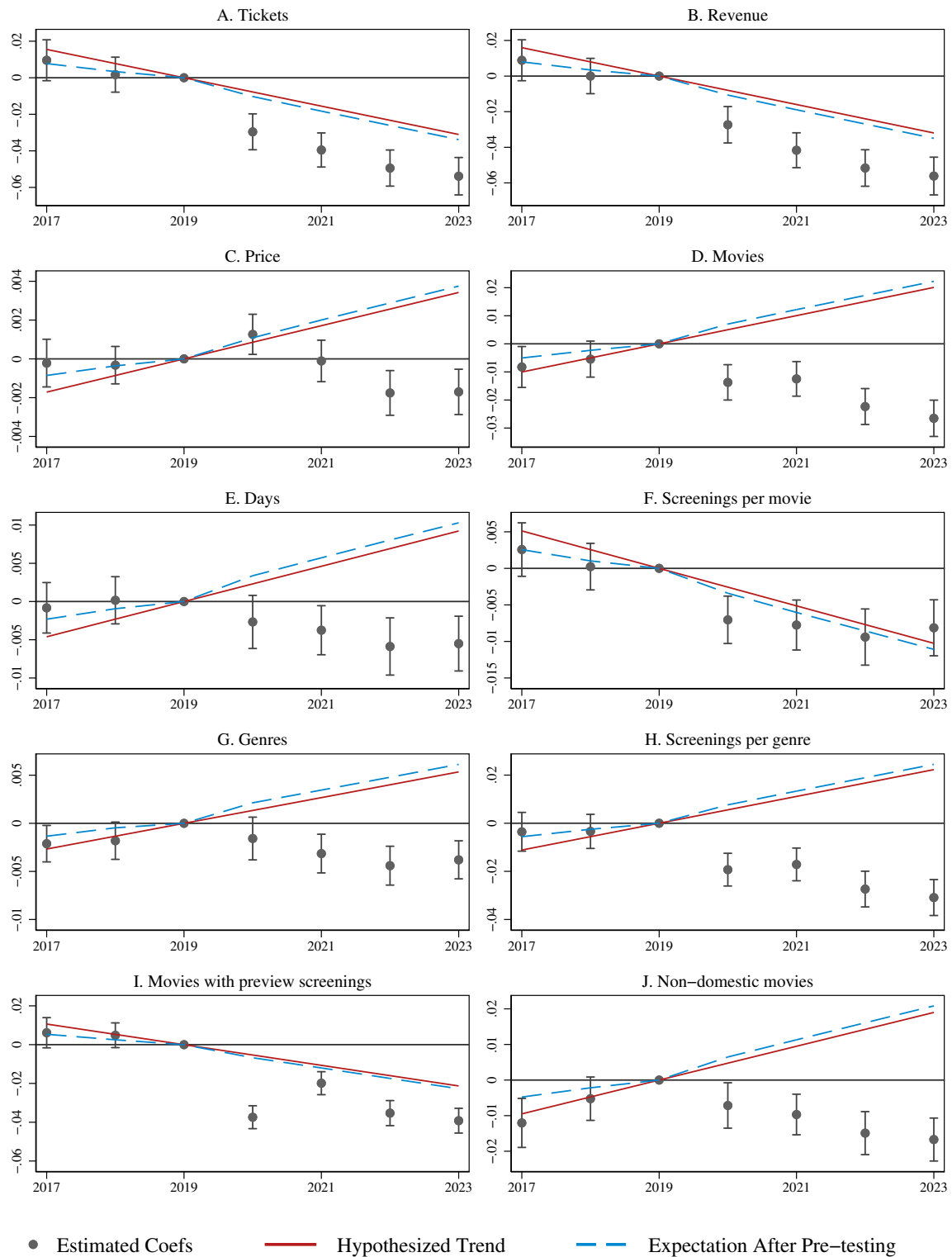


Figure A5: Pre-Trend Sensitivity Analysis, 80 Percent Power

Notes: This figure overlays pre-trend sensitivity analysis from Roth (2022) on the event-study estimates from Figures 2 and 3. Each panel corresponds to a different outcome variable. The solid red lines show the positive linear pre-trend detectable with 80 percent power. The dashed blue lines show the post-treatment coefficients that would arise under this linear trend when no significant pre-trend is detected. In nearly all panels, the simulated coefficients (dashed blue) fall outside the post-COVID confidence intervals, suggesting that estimated treatment effects are unlikely to be driven by spurious pre-trends. The reference year is 2019. All variables are in logs; population density is measured in 2016.

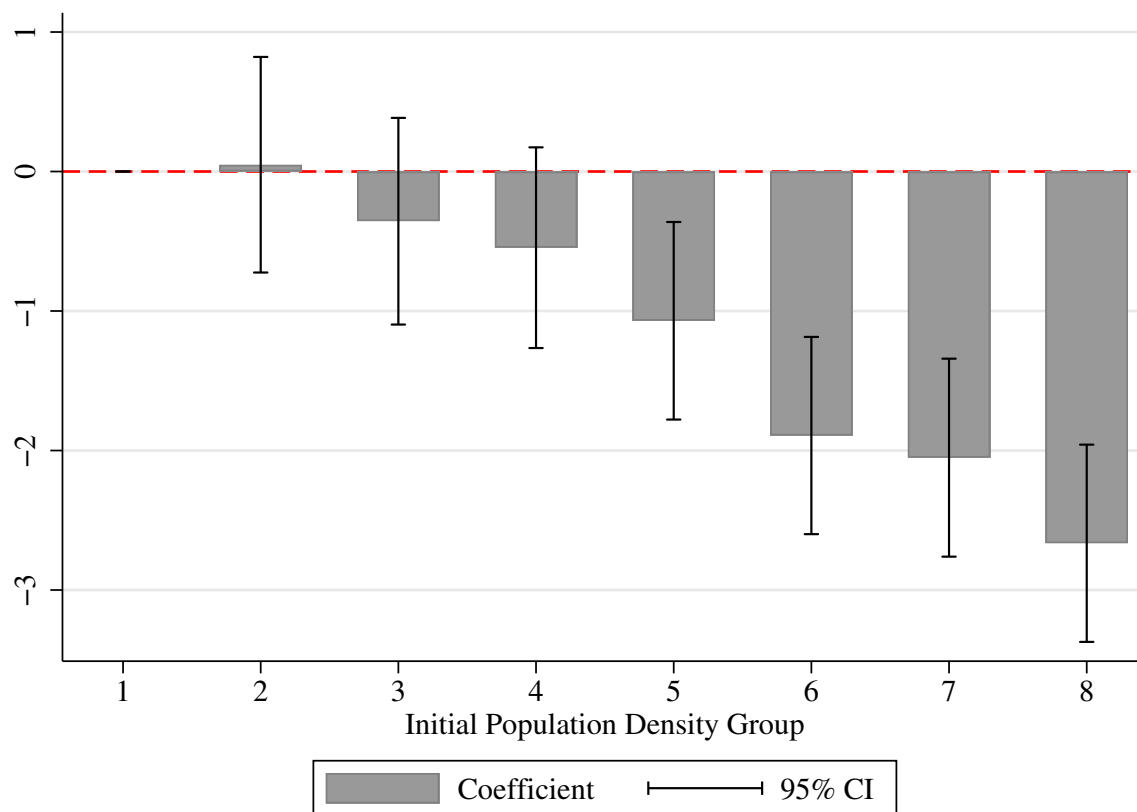


Figure A6: Assessing Monotonicity: Post-COVID Population Change by Initial Density (Eight Groups)

Notes: This figure assesses the monotonicity assumption by plotting the post-COVID change in log population across eight initial-density groups. Each coefficient and its 95% confidence interval are from a difference-in-differences specification that regresses contemporaneous log population density on the interaction of initial population density group indicators (measured in 2016) with a post-2020 indicator, controlling for grid and year fixed effects. Initial population density is divided into eight equal-sized groups, with the lowest-density group serving as the reference category. Standard errors are clustered at the grid level. The sample uses grid-level data (approximately 800m × 800m) from 2017 to 2023.

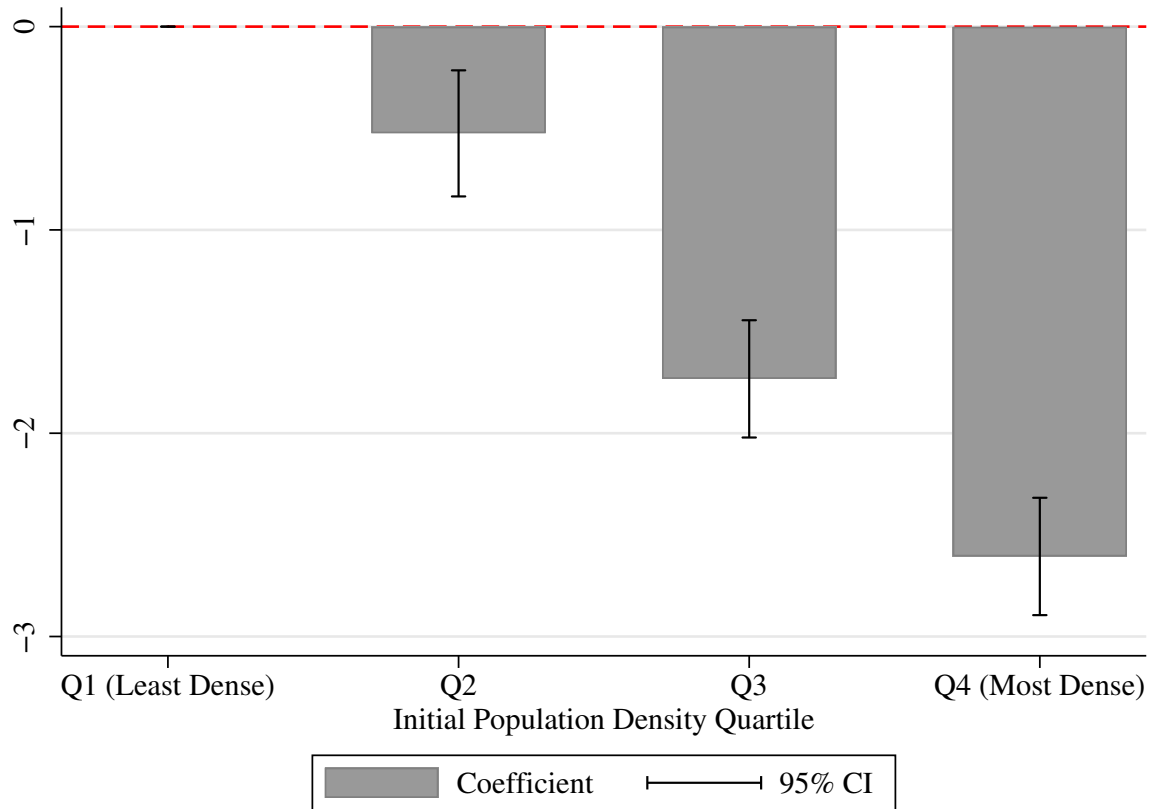


Figure A7: Assessing Monotonicity: Post-COVID Population Change by Initial Density (Four Groups)

Notes: This figure assesses the monotonicity assumption by plotting the post-COVID change in log population across four initial-density groups. Each coefficient and its 95% confidence interval are from a difference-in-differences specification that regresses contemporaneous log population density on the interaction of initial population density group indicators (measured in 2016) with a post-2020 indicator, controlling for grid and year fixed effects. Initial population density is divided into four equal-sized groups, with the lowest-density group serving as the reference category. Standard errors are clustered at the grid level. The sample uses grid-level data (approximately 800m \times 800m) from 2017 to 2023.

Table A1: Summary Statistics

Variable	Mean	Median	SD.	Obs.
Population (2016)	41,048.31	3,750.50	46,220.84	90,825
Population (2017-2023)	39,668.23	3,750.50	45,704.45	90,825
Tickets (thousand)	96.74	38.66	158.91	90,825
Revenue (thousand CNY)	3,656.54	1,389.31	6,317.03	90,825
Price	28.50	33.93	17.76	90,825
Movies	133.85	142.00	96.53	90,825
Days	18.84	20.79	12.58	90,825
Screenings per movie	43.94	44.45	37.40	90,825
Genres	17.67	23.00	9.80	90,825
Screenings per genre	345.81	285.96	357.31	90,825
Movies with preview screenings	16.70	13.00	17.66	90,825
Non-domestic movies	47.06	47.00	36.49	90,825

Notes: This table reports summary statistics for the main variables used in the analysis. Each grid cell is approximately 800m \times 800m, based on the LandScan database. Population (2016) is measured at the grid level for the year 2016; Population (2017–2023) is measured at the grid-year level. Movie outcomes are constructed from the China Movie Database and measured at the grid-year level for 2017–2023. Ticket sales and box office revenue are reported in thousands.

Table A2: Density Premiums for Movie Consumption (Contemporaneous Population, 2017-2019)

	(1)	(2)
<i>Panel A. Tickets</i>		
log(pop)	0.2066*** (0.0070)	0.1613*** (0.0065)
Adjusted R-squared	0.072	0.265
Obs.	26,982	26,982
<i>Panel B. Revenue</i>		
log(pop)	0.2084*** (0.0072)	0.1597*** (0.0067)
Adjusted R-squared	0.070	0.266
Obs.	26,984	26,984
<i>Panel C. Price</i>		
log(pop)	0.0017*** (0.0006)	-0.0018*** (0.0005)
Adjusted R-squared	0.047	0.244
Obs.	26,982	26,982
Year FE	Yes	Yes
City FE	No	Yes

Notes: This table reports OLS estimates of the cross-sectional relationship between contemporaneous population density and movie consumption outcomes in the pre-pandemic period (2017–2019). Each regression regresses log outcomes on log contemporaneous population density, controlling for fixed effects. Panel A: ticket sales; Panel B: box office revenue; Panel C: average ticket price. Column (1) includes year fixed effects only; Column (2) adds city fixed effects. Standard errors clustered at the grid level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Density Premiums for Varieties (Contemporaneous Population, 2017-2019)

	(1)	(2)
<i>Panel A. Movies</i>		
log(pop)	0.0362*** (0.0021)	0.0323*** (0.0021)
Adjusted R-squared	0.017	0.043
Obs.	27,037	27,037
<i>Panel B. Days</i>		
log(pop)	0.0237*** (0.0015)	0.0198*** (0.0014)
Adjusted R-squared	0.045	0.134
Obs.	27,037	27,037
<i>Panel C. Screenings per movie</i>		
log(pop)	0.0752*** (0.0030)	0.0602*** (0.0028)
Adjusted R-squared	0.063	0.233
Obs.	27,037	27,037
<i>Panel D. Genres</i>		
log(pop)	0.0061*** (0.0005)	0.0057*** (0.0006)
Adjusted R-squared	0.016	0.024
Obs.	27,037	27,037
<i>Panel E. Screenings per genre</i>		
log(pop)	0.1053*** (0.0041)	0.0868*** (0.0040)
Adjusted R-squared	0.056	0.175
Obs.	27,037	27,037
<i>Panel F. Movies with preview screenings</i>		
log(pop)	0.0952*** (0.0038)	0.0734*** (0.0035)
Adjusted R-squared	0.091	0.249
Obs.	25,973	25,971
<i>Panel G. Non-domestic movies</i>		
log(pop)	0.0325*** (0.0019)	0.0290*** (0.0019)
Adjusted R-squared	0.028	0.052
Obs.	26,902	26,902
Year FE	Yes	Yes
City FE	No	Yes

Notes: This table reports OLS estimates of the cross-sectional relationship between contemporaneous population density and movie variety outcomes in the pre-pandemic period (2017–2019). Each regression regresses log outcomes on log contemporaneous population density, controlling for fixed effects. Panel A: number of movies; Panel B: days on screen; Panel C: screenings per movie; Panel D: number of genres; Panel E: screenings per genre; Panel F: movies with preview screenings; Panel G: number of non-domestic movies. Column (1) includes year fixed effects only; Column (2) adds city fixed effects. Standard errors clustered at the grid level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Density Premiums for Movie Consumption (2SLS)

	(1)	(2)
<i>Panel A. Tickets</i>		
log(pop)	0.1849*** (0.0066)	0.1854*** (0.0162)
Cragg-Donald F stat	93,232	4,756
Obs.	69,944	69,194
<i>Panel B. Revenue</i>		
log(pop)	0.1831*** (0.0067)	0.1864*** (0.0167)
Cragg-Donald F stat	93,230	4,758
Obs.	69,961	69,211
<i>Panel C. Price</i>		
log(pop)	-0.0022*** (0.0005)	0.0014 (0.0018)
Cragg-Donald F stat	93,232	4,756
Obs.	69,944	69,194

Notes: This table reports 2SLS estimates of the effect of population density on movie consumption using grid-year data from 2017–2023. The dependent variable is the log of movie consumption outcomes. The endogenous regressor, log contemporaneous population density, is instrumented with the interaction of pre-sample (2016) population density and a post-pandemic indicator. Standard errors clustered at the grid level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Density Premiums for Varieties (2SLS)

	(1)	(2)
<i>Panel A. Movies</i>		
log(pop)	0.0386*** (0.0019)	0.0585*** (0.0091)
Cragg-Donald F stat	93,457	4,764
Obs.	70,136	69,395
<i>Panel B. Days</i>		
log(pop)	0.0267*** (0.0014)	0.0172*** (0.0049)
Cragg-Donald F stat	93,457	4,764
Obs.	70,136	69,395
<i>Panel C. Screenings per movie</i>		
log(pop)	0.0728*** (0.0029)	0.0360*** (0.0060)
Cragg-Donald F stat	93,457	4,764
Obs.	70,136	69,395
<i>Panel D. Genres</i>		
log(pop)	0.0075*** (0.0005)	0.0081*** (0.0027)
Cragg-Donald F stat	93,451	4,764
Obs.	70,133	69,392
<i>Panel E. Screenings per genre</i>		
log(pop)	0.1039*** (0.0039)	0.0866*** (0.0110)
Cragg-Donald F stat	93,451	4,764
Obs.	70,133	69,392
<i>Panel F. Movies with preview screenings</i>		
log(pop)	0.0743*** (0.0030)	0.1454*** (0.0107)
Cragg-Donald F stat	89,110	4,660
Obs.	67,591	66,767
<i>Panel G. Non-domestic movies</i>		
log(pop)	0.0366*** (0.0017)	0.0278*** (0.0090)
Cragg-Donald F stat	92,828	4,725
Obs.	69,626	68,888

Notes: This table presents 2SLS estimates of the effect of population density on movie variety using grid-year data from 2017–2023. The dependent variable is the log of movie variety outcomes. The endogenous regressor, log contemporaneous population density, is instrumented with the interaction of pre-sample (2016) population density and a post-pandemic indicator. Standard errors clustered at the grid level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Assessing Monotonicity of First-Stage Estimates by City-Density Quartile

	(1)	(2)	(3)	(4)
After \times log(pop)	-0.2752*** (0.0087)	-0.2732*** (0.0086)	-0.2558*** (0.0078)	-0.2324*** (0.0084)
Cities	Q1 (Least Dense)	Q2	Q3	Q4 (Most Dense)
Year FE	Yes	Yes	Yes	Yes
Grid FE	No	Yes	Yes	Yes
Adjusted R-squared	0.904	0.897	0.905	0.907
Obs.	22,581	22,666	22,687	22,442

Notes: This table assesses the monotonicity assumption by reporting the first-stage relationship separately across city-density quartiles. Each column regresses contemporaneous log population density on the interaction of log population density (measured in 2016) and a post-2020 indicator, using grid-level data (approximately 800m \times 800m) from 2017 to 2023. Cities are grouped into four quartiles based on their average grid-level population density in 2016, from Q1 (least dense) to Q4 (most dense). All specifications include year fixed effects; grid fixed effects are included in Columns (2)–(4) but not in Column (1). Standard errors clustered at the grid level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Changes in Initial-Density Gradients for Movie Consumption, Excluding Lock-down Years

	(1)	(2)
<i>Panel A. Tickets</i>		
log(pop)	0.1595*** (0.0064)	
After × log(pop)	-0.0216*** (0.0062)	-0.0485*** (0.0050)
Adjusted R-squared	0.255	0.785
Obs.	38,012	35,181
<i>Panel B. Revenue</i>		
log(pop)	0.1577*** (0.0065)	
After × log(pop)	-0.0210*** (0.0064)	-0.0498*** (0.0052)
Adjusted R-squared	0.251	0.784
Obs.	38,016	35,186
<i>Panel D. Price</i>		
log(pop)	-0.0019*** (0.0005)	
After × log(pop)	0.0004 (0.0006)	-0.0012** (0.0006)
Adjusted R-squared	0.394	0.727
Obs.	38,012	35,181

Notes: This table reports robustness estimates after excluding the lockdown years 2020–2022, using data from 2017–2019 and 2023 only. Each regression regresses log outcomes on the interaction of log population density (measured in 2016) and a post-2020 indicator, controlling for fixed effects. Panel A: ticket sales; Panel B: box office revenue; Panel D: average ticket price. Column (1) includes year and city fixed effects; Column (2) includes year and grid fixed effects. Standard errors clustered at the grid level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Changes in Initial-Density Gradients for Varieties, Excluding Lockdown Years

	(1)	(2)
<i>Panel A. Movies</i>		
log(pop)	0.0323*** (0.0021)	
After × log(pop)	-0.0021 (0.0029)	-0.0174*** (0.0030)
Adjusted R-squared	0.068	0.312
Obs.	38,104	35,271
<i>Panel B. Days</i>		
log(pop)	0.0195*** (0.0014)	
After × log(pop)	0.0059*** (0.0019)	-0.0046*** (0.0017)
Adjusted R-squared	0.268	0.637
Obs.	38,104	35,271
<i>Panel C. Screenings per movie</i>		
log(pop)	0.0596*** (0.0028)	
After × log(pop)	0.0001 (0.0026)	-0.0073*** (0.0020)
Adjusted R-squared	0.228	0.844
Obs.	38,104	35,271
<i>Panel D. Genres</i>		
log(pop)	0.0054*** (0.0005)	
After × log(pop)	0.0022*** (0.0008)	-0.0010 (0.0008)
Adjusted R-squared	0.032	0.250
Obs.	38,104	35,271
<i>Panel E. Screenings per genre</i>		
log(pop)	0.0866*** (0.0039)	
After × log(pop)	-0.0042 (0.0043)	-0.0238*** (0.0036)
Adjusted R-squared	0.163	0.681
Obs.	38,104	35,271
<i>Panel F. Movies with preview screenings</i>		
log(pop)	0.0751*** (0.0034)	
After × log(pop)	-0.0314*** (0.0036)	-0.0373*** (0.0033)
Adjusted R-squared	0.234	0.656
Obs.	36,744	33,838
<i>Panel G. Non-domestic movies</i>		
log(pop)	0.0286*** (0.0019)	
After × log(pop)	0.0045 (0.0028)	-0.0085*** (0.0029)
Adjusted R-squared	0.165	0.354
Obs.	37,885	35,059

Notes: This table reports robustness estimates after excluding the lockdown years 2020–2022, using data from 2017–2019 and 2023 only. Each regression regresses log outcomes on the interaction of log population density (measured in 2016) and a post-2020 indicator, controlling for fixed effects. Panel A: number of movies; Panel B: days on screen; Panel C: screenings per movie; Panel D: number of genres; Panel E: screenings per genre; Panel F: movies with preview screenings; Panel G: number of non-domestic movies. All dependent variables are in logs. Column (1) includes year and city fixed effects; Column (2) includes year and grid fixed effects. Standard errors clustered at the grid level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Visits per Capita to Cinema-Related Grid Cells in Shanghai

	(1)	(2)	(3)	(4)
<i>Panel A. At least five residents</i>				
After \times ln(pop in 2019)	0.277*** (0.004)	0.264*** (0.004)	0.076*** (0.003)	0.291*** (0.004)
Grid FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.31	0.31	0.40	0.34
Obs.	116,896	117,794	173,780	113,400
<i>Panel B. At least ten residents</i>				
After \times ln(pop in 2019)	0.224*** (0.005)	0.208*** (0.005)	0.022*** (0.004)	0.242*** (0.005)
Grid FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.33	0.33	0.46	0.36
Obs.	105,102	105,556	137,290	102,506

Notes: All regressions follow Equation (1) except that the dependent variable is the logarithm of visits per capita to grid cells containing cinemas or nearby locations. The indicator variable “After” equals one for 2024 and zero for 2019. In all columns, visits are restricted to non-home and non-work trips lasting at least 90 minutes. Column 1 considers visits to grid cells with cinemas as of 2019, Column 2 accounts for visits to grid cells with cinemas in the corresponding year, Column 3 includes visits to grid cells within 100 meters of cinemas in 2019, and Column 4 restricts visits to those lasting no more than 360 minutes. The sample is restricted to grid cells with at least five residents in Panel A and at least ten residents in Panel B, for both 2019 and 2024. Standard errors, clustered at the grid-cell level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Per-Capita Video App Usage in Shanghai

	(1) Cellular data At least five residents	(2) Time	(3) Cellular data At least ten residents	(4) Time
After \times ln(pop in 2019)	-0.225*** (0.005)	-0.486*** (0.006)	-0.242*** (0.006)	-0.454*** (0.007)
Grid FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.11	0.53	0.12	0.56
Obs.	203,164	204,796	144,640	145,008

Notes: All regressions follow Equation (1) except that the dependent variable is the logarithm of per-capita video app usage, measured either as the total data consumed or the total time spent on the three most popular video apps, divided by the population in each grid cell. In Columns 1 and 3, the dependent variable is the logarithm of monthly data usage per capita, whereas in Columns 2 and 4, it is the logarithm of monthly time spent per capita. The indicator variable “After” equals one for 2024 and zero for 2019. The sample is restricted to grid cells with at least five residents in Columns 1 and 2, and at least ten residents in Columns 3 and 4, for both years. Standard errors, clustered at the grid-cell level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.