A Work Project, presented as part of the requirements for the Award of a Master's degree in **Business Analytics** from the Nova School of Business and Economics.

THE POWER OF BEING SEEN

The Impact of Google Street View on Urban Development in the United States - Crime & Education Outcomes

Laura Volpe

Work project carried out under the supervision of:

Michail Batikas

26-01-2026

Abstract

This paper examines whether digital visibility affects urban development by studying the staggered rollout of Google Street View (GSV) across U.S. cities. Treating GSV as an informational shock, the analysis uses staggered Difference-in-Differences estimators to estimate causal effects on urban expansion, housing markets, tourism, population, crime, and education. Results show that GSV has modest but meaningful effects in domains closely tied to perception and information, such as tourism activity, housing prices, and selected crime outcomes, while effects on population and employment are limited. Overall, digital visibility matters, but its impacts are heterogeneous and generally moderate.

Keywords

Google Street View; Causal Inference; Difference-in-Differences; Urban Expansion; Finance Outcomes; Tourism; Population; Crime; Education.

This work was funded by Fundação para a Ciência e a Tecnologia (UID/00124/2025, UID/PRR/124/2025, Nova School of Business and Economics) and LISBOA2030 (DataLab2030 - LISBOA2030-FEDER-01314200).

1. Introduction

Over the past two decades, digital platforms have become core infrastructures through which urban space is perceived and navigated. Online maps, navigation tools, review platforms and social media increasingly mediate interactions with cities that once relied on direct physical experience. Roads, neighborhoods and entire urban areas are often first encountered through satellite imagery, street-level views and user-generated content. As a result, contemporary urban life unfolds simultaneously in a physical space and a digital layer that shapes visibility and perception.

This transformation raises a central question in urban and economic research: does digital visibility merely reflect urban realities, or does it actively influence urban development?

When detailed visual and contextual information, such as greenery, building quality or perceived safety, is globally accessible at low cost, it may systematically affect decisions of residents, firms, visitors and policymakers. Housing choices, investment, tourism behavior, policing strategies and infrastructure placement can all be influenced by readily available online information. If these effects are persistent and non-random, changes in digital exposure may translate into measurable urban outcomes.

Google Street View (GSV) provides a suitable setting to study this mechanism. Integrated into Google Maps and Google Earth, GSV allows users to virtually access high-resolution street-level imagery of cities worldwide. Its rollout marked a shift in digital visibility: once mapped, cities became immediately observable to a global audience. GSV was introduced gradually rather than simultaneously. In the United States, cities gained Street View coverage between 2007 and 2010, while key urban indicators are recorded annually. This staggered rollout generates variation in the timing of exposure to digital street-level visibility, creating a natural experimental framework to study GSV as an information shock.

Group Part

The objective of this research is to assess whether the introduction of Google Street View has influenced urban outcomes. The analysis focuses on six dimensions of urban development: urban expansion, financial outcomes, tourism, population dynamics, crime and education infrastructure. Drawing on the literature on digital platforms, GSV is conceptualized as operating through three main channels: reduced information and search costs, increased visibility and perceived value, and spatial sorting accompanied by behavioral and institutional responses to greater transparency. Based on these mechanisms, domain-specific hypotheses aim to examine whether earlier exposure to GSV is associated with differential urban trajectories across these outcomes.

Existing research offers relevant insights but also reveals limitations. Street-level imagery is widely used to measure urban environments, and studies on digital platforms emphasize the role of geospatial data in transparency and innovation. However, GSV is typically treated as a measurement tool rather than as a phased intervention that alters public visibility. Moreover, much of the literature remains domain-specific, lacking a unified framework linking digital visibility to outcomes such as tourism, demographics, crime, education and financial outcomes.

This analysis contributes by reframing GSV as a staggered informational shock and linking its rollout to panel data covering a broad set of urban indicators, moving beyond cross-sectional correlations. It integrates insights from research on digital platforms, image-based data and domain-specific studies into a mechanism-driven framework centered on search costs, visibility and spatial sorting. Methodologically, the analysis employs staggered Difference-in-Differences (DiD) approaches, specifically Callaway-Sant'Anna (CS) group-time average treatment effects and Sun-Abraham (SA) event-study estimators implemented in PyFixest, addressing biases associated with treatment heterogeneity and phased adoption that affect the traditional Two-Way Fixed Effect (TWFE) model used as a first analysis.

Empirically, the study constructs city-year panels combining GSV launch dates with outcome measures from public agencies, federal records and specialized databases. Separate but harmonized datasets are thus developed for each domain.

The main estimand is the Average Treatment Effect on the Treated (ATT), defined as the post-GSV change in outcomes relative to the counterfactual trajectory of not-yet-treated cities.

The remainder of the thesis is organized as follows. Section 2 reviews the literature, develops the mechanism-based framework and positions GSV as an informational shock. Section 3 presents the hypotheses. Section 4 describes the data and empirical strategy. Subsequent chapters report the results across domains. The research concludes by situating the findings within broader debates on digital platforms and urban development, discussing policy implications and directions for future research on digital visibility in cities.

2. Literature Review

2.1. Research Question & Scope

In the last twenty years, rapid expansion of digital technologies has transformed how people access information and interact with urban environments. Digital platforms, ranging from social media to navigation tools and geospatial mapping services, now mediate many aspects of urban experience, adding a digital layer alongside direct physical interaction. This transformation raises a central question in urban and economic research, about whether digital visibility merely reflects underlying urban conditions or actively shapes urban development through identifiable mechanisms.

The paper investigates how digital mapping platforms and street-level imagery influence urban outcomes, focusing specifically on the rollout of Google Street View. It examines whether GSV has had a causal and measurable impact across the six domains of urban development mentioned in the Introduction section. By concentrating on a single platform with staggered adoption across cities, the analysis seeks to isolate the role of digital visibility in shaping urban trajectories.

2.2. How Digital Platforms Affect Urban Outcomes: Theoretical Mechanisms

To understand how digital platforms may shape urban outcomes, it is necessary to examine the mechanisms through which digital visibility and accessible spatial information influence behavior and generate measurable changes.

2.2.1. Reductions in Information Frictions & Search Costs

A key feature of digital platforms is their capacity to make information widely accessible, reducing frictions that historically constrained urban decision-making. Research on Open Government Data shows that freely available information lowers barriers to acquiring reliable data, leading to reduced information asymmetries, more efficient decisions, and the development of new data-driven services (Wirtz, et al. 2022). Related work links open data availability to higher levels of digital entrepreneurship, with effects shaped by institutional environments (Huber, et al. 2022).

In the urban context, advances in geospatial big data further illustrate how richer spatial information reshapes decision environments. Integrated datasets, including satellite imagery, location-aware sensors, and mobility traces, enable detailed modeling of population distribution, land use, environmental conditions, and human-city interactions that were previously difficult to observe (Wu, Gui and Yang 2020). At the same time, open-source geospatial tools have lowered technical barriers, allowing smaller organizations and individuals to conduct analyses once limited to specialized agencies (Mobasheri, Pirotti and Agugiaro 2020).

Taken together, this literature highlights a fundamental mechanism through which digital platforms affect urban outcomes: by increasing the availability, accessibility, and usability of spatial information, they expand the set of locations and opportunities that households, firms, and institutions can meaningfully consider, thereby reshaping urban decision-making processes.

2.2.2. Enhanced Visibility, Visual Signaling and Reputation

Digital platforms determine not only *what* information is available, but also *how* it is presented, and consequently interpreted. Features such as visual previews and street-level imagery influence perceptions that previously required physical presence. By directing attention toward specific neighborhoods or amenities, platforms act as intermediaries that shape the informational signals on which urban actors rely.

A substantial body of research demonstrates that platform-mediated visibility can influence economic outcomes through signaling and reputational effects. For example, studies on hotel ratings show that higher platform scores increase revenues by signaling quality to consumers and by building reputation over time (Sayfuddin and Chen 2021). This evidence suggests that digital platforms do not merely reflect underlying conditions but actively shape perceptions and behavior.

Related research in urban economics shows that visual environmental characteristics are capitalized into housing prices. Zhang and Dong (2018) document that street-visible greenery significantly increases housing values in Beijing, while Law, Paige, and Russell (2019) demonstrate that incorporating Google Street View and aerial imagery into hedonic models improves house-price prediction by capturing neighborhood characteristics that conventional datasets fail to observe. These studies indicate both that visual features matter for economic outcomes and that digital imagery enhances how such features are perceived and evaluated.

This literature provides a foundation for examining whether changes in digital visibility, such as the introduction of GSV, can influence housing markets and related urban outcomes.

2.2.3. Spatial Sorting and Matching

Digital platforms also affect urban outcomes by facilitating spatial sorting and matching. When information becomes easier to access and compare, households, firms, and tourists can better align their choices with preferred locations. Improved matching can influence residential mobility, firm location decisions, and tourism flows.

Much of the literature has used geotagged social media data to measure visitation patterns and spatial use, demonstrating the value of digital traces for monitoring individuals' behavior while also highlighting representativeness biases (Wilkins, Wood and Smith 2021).

Although much of this work treats social media as a measurement tool, emerging evidence suggests that user-generated content can also influence, for instance, tourist behavior by shaping destination imagery. Photos, reviews, and posts shared by users affect tourists' intentions by reshaping the cognitive and emotional images they associate with places (Aboalganam, AlFraihat and Tarabieh 2025).

While causal evidence exists for the influence of social media representations, less is known about how other forms of digital visual information, particularly street-level imagery, affect spatial choices. This gap motivates the present study's focus on Google Street View as a distinct form of digital visibility that may influence spatial sorting, destination choice, and urban behavior.

2.3. Google Street View as a Specific Informational Shock

Google Street View is a clear example of digital visibility as an informational shock. Embedded in Google Maps and Google Earth, GSV allows users to virtually explore streets through high-resolution imagery, making micro-level cues about safety, upkeep, greenery, and streetscape quality observable at very low cost. Prior research shows that GSV-based virtual audits can reliably substitute for in-person observation when assessing built-environment characteristics (Rundle, et al. 2011, Odgers, et al. 2012). Advances in computer vision have further enabled researchers to extract large-scale indicators from millions of GSV images, linking streetscape features to outcomes such as public health (Nguyen, et al. 2019).

Compared to conventional web maps or satellite imagery, GSV provides particularly rich visual information. Law, Paige, and Russell (2019) show that street-level imagery captures aesthetic and maintenance-related characteristics, often described as “visual desirability”, that are not well represented in standard geographic information systems data. This informational richness suggests that GSV may influence not only measurement but also perception and decision-making.

GSV has also attracted attention in criminology. Vandeviver (2014) reviews the potential use of Google Maps and Street View in environmental criminology, while Van Daele et al. (2012) provide an experimental study examining how street-level imagery may influence burglary target selection in a simulated setting. Although the evidence is limited and does not support strong conclusions about real-world offender behavior, it highlights a significant gap in understanding how digital mapping platforms may affect crime-related decision-making.

Overall, this literature supports treating the staggered rollout of Google Street View not merely as a data source, but as a structural change in what households, firms, tourists, and institutions can observe, directly linking GSV to the mechanisms of reduced information frictions, enhanced visibility, and spatial sorting outlined in section 2.2.

2.4. Research Gap and Contribution

Within broader literature, Google Street View has primarily emerged as a valuable assessment instrument. However, its use as a data source raises important methodological considerations: coverage is uneven across space and time, and imagery dates vary substantially, requiring careful treatment of metadata and temporal alignment in empirical applications (Curtis, et al. 2013).

In criminology, GSV and Google Maps have been discussed as potentially relevant tools for environmental analysis and target assessment (Vandeviver 2014). However, empirical research in this domain is still extremely limited, pointing to a substantial research gap in understanding how GSV might influence offender decision-making or lead to changes in local crime patterns. More broadly, this limitation reinforces the argument that the influence of digital mapping platforms remains underexplored and fits within a wider turn toward imagery and remote sensing in the social sciences, an approach that offers fine-grained urban measurement but raises unresolved issues related to causality, coverage, and bias (Wang 2024).

Nevertheless, additional gap persists. The existing literature overwhelmingly treats Google Street View as a static measurement tool rather than as a dynamic intervention that alters what is publicly visible about cities over time.

As previously mentioned in section 1, the present analysis addresses this gap by conceptualizing GSV deployment as an informational shock and integrating literature on open data, digital platforms, imagery-based assessment and domain-specific applications into a common mechanism-based framework, and using a DiD design that exploits variation in GSV adoption timing across cities to estimate its effects on urban development.

3. Hypotheses Development

3.1. Crime

H-Crime. *Google Street View availability affects overall theft value, causing either an increase or decrease in treated cities.*

Group Part

The criminological literature suggests that Google Street View may meaningfully alter the informational environment in which criminal behavior occurs. As discussed in the Literature Review section, Vandeviver (2014) shows that digital mapping platforms introduce new dynamics into environmental criminology by making detailed, street-level information widely accessible to both offenders and law-enforcement agencies.

Complementing this, the study by Van Daele et al. (2012), involving criminology students in a simulated task, provides initial experimental evidence that street-level imagery can be used to evaluate environmental cues relevant for burglary target selection, such as accessibility, visibility, and escape routes. Yet, as Vandeviver emphasizes, the criminological implications of such platforms remain mostly unexplored, revealing a substantial gap in empirical research. Addressing this gap provides a key motivation for the present analysis, which seeks to specifically examine whether the rollout of GSV has had a measurable effect on crime levels in major U.S. cities.

This need for deeper investigation is reinforced by Europol's *Crime in the Age of Technology* report (Europol 2017), which documents how criminal organizations increasingly rely on publicly available geospatial data for reconnaissance and operational planning. At the same time, digital mapping technologies enhance the capabilities of law-enforcement agencies by supporting environmental audits, hotspot identification, and improved situational awareness. Therefore, GSV represents a dual-use informational shock: it lowers informational barriers for offenders while simultaneously strengthening institutional deterrence and monitoring capacity.

Taken together, these developments suggest that the introduction of Google Street View may have altered how both offenders and institutions perceive and respond to urban environments, leading to the expectation that GSV should have measurable effects on crime outcomes.

This yields the primary hypothesis: *Google Street View availability affects the total value of theft offenses in treated cities.* In addition to this main expectation, the underlying *property- and opportunity-driven offenses than for severe violent crimes,* as the former are more sensitive to changes in perceived accessibility, guardianship, and environmental visibility.

3.2. Education

H-Education. *Google Street View affects educational patterns in treated cities by altering the perception of public spaces and neighborhoods, leading to measurable changes in variables such as number of students and number of schools per city.*

The mechanisms discussed in the literature review suggest that digital visibility can influence how individuals and institutions evaluate neighborhoods, shaping decisions about where to live, invest, or establish services. These dynamics extend to the education sector. As highlighted earlier, digital mapping platforms such as Google Street View make neighborhood characteristics more transparent to the public. This enhanced visibility may influence parental school-choice decisions, residential sorting around schools, and institutional responses by local education providers.

Existing research on school choice consistently shows that families rely heavily on neighborhood cues and perceived environmental quality when selecting educational institutions, and these perceptions affect enrolment patterns and the spatial distribution of demand for schooling (Burgess, et al. 2015). Furthermore, studies examining the use of geospatial information in education, such as UNESCO's initiatives advancing geospatial tools for education management (UNESCO International Institute for Educational Planning), suggest that spatial data increasingly supports educational decision-making, resource allocation, and institutional planning.

In this context, the rollout of GSV represents an informational shift that may alter how both households and educational institutions perceive neighborhood desirability and local service quality. Increased digital visibility may make certain areas appear more attractive or better connected, potentially strengthening demand for nearby schools, influencing enrolment trajectories, or shaping where new educational facilities are established. Conversely, areas that appear visually neglected or unsafe in street-level imagery may experience reduced parental interest and weaker institutional investment. Together, these considerations motivate the hypothesis that the introduction of Google Street View may influence observable educational patterns within cities by modifying the informational landscape surrounding school choice and neighborhood desirability.

4. Data

4.1. Research Question

The central aim of this thesis is to estimate whether the introduction of Google Street View has a causal effect on different urban outcomes. The focus is on urban expansion, such as the overall population size; financial outcomes, such as the price of houses; city population dynamics, such as the number of registered cars; tourism indicators, such as hotel capacity and the number of tourist attractions; crime patterns, such as the number of violent crimes; and education, such as the number of students and schools.

The main parameters of interest are average treatment effects of GSV on these outcomes, with particular attention to the Average Treatment Effect on the Treated (ATT): the average change in outcomes for cities after they receive GS, relative to how those outcomes would have evolved in the absence of GSV.

By estimating separate effects for different variable measures, the analysis aims to shed light not only on whether GSV has a significant impact, but also which aspects of city development it appears to influence.

4.2. Empirical Strategy: Modern Staggered Difference-in-Differences

Google Street View rollout is documented using first-coverage months and years, extracted from the Wikipedia page "Google Street View in the United States" (Wikipedia). All cities in the sample eventually receive GSV, but at different times between 2007 and 2010, while variables are observed annually from 2000 to 2018, with the range differing depending on the variable analyzed. Data is thus organized as a city-year panel with a first treatment year for each city, and an event-time variable (years relative to first treatment) is used to trace pre- and post-treatment dynamics in event-study form.

Additionally, city-specific rollout years and months are used to define a binary treatment indicator GSV_{it}, which equals 1 in all years in which Street View is effectively available in city i. If rollout occurs before June of year t, GSV_{it} switches to 1 in year t; if rollout occurs in the second half of year t, it switches to 1 from year $t+1$. This convention aligns treatment timing with the annual frequency of the data and avoids overstating exposure in years with only partial coverage.

The core challenge is to recover the causal effect of GSV in a staggered adoption setting with potentially heterogeneous treatment effects. The analysis therefore relies on modern DiD methods rather than a single Two-Way Fixed Effects regression. Across all approaches, the main estimand is the Average Treatment Effect on the Treated (ATT).

Two complementary estimators are used. First, a Callaway-Sant'Anna group-time DiD design estimates cohort-specific and event-time ATTs by comparing cities treated in a given year to not-yet-treated cities, and then aggregates these into overall and dynamic effects. Second, an event-study estimator in the spirit of Sun and Abraham is implemented via PyFixest, using unit and time fixed effects and relative-time dummies, and correcting standard TWFE event-study coefficients for staggered-adoption bias. For completeness, conventional TWFE specifications are also estimated as a benchmark, but given their known limitations under staggered and heterogeneous treatment, substantive conclusions are based on the modern DiD estimators.

4.3. Crime

4.3.1. Data Sources

The crime data used in this thesis is constructed from datasets that are part of the Uniform Crime Reporting (UCR) Program. The primary source is the *Offenses Known and Clearances by Arrest* database (United States. Federal Bureau of Investigation. 2022), archived at the National Archives of Criminal Justice Data (NACJD) and analyzed on The Marshall Project, which compiled the most recent UCR numbers available on the four major crimes the FBI classifies as violent: homicide, rape, robbery and assault (Dance, Meagher and Hopkins 2016).

The *Property Stolen and Recovered* dataset (United States. Federal Bureau of Investigation. 2023), another component of the UCR system, complements this data. This dataset provides detailed information on the number of offenses, the monetary value of stolen property, and the breakdown of offenses into subcategories. For instance, the robbery category is disaggregated into highway robbery, bank robbery, gas-station robbery, and other specific contexts, while theft is divided into categories such as shoplifting, bicycle theft, theft from buildings, purse snatching, and theft from automobiles. For each category, the dataset additionally reports the value of stolen property, and the value of property recovered.

4.3.2. Data Preprocessing

The crime dataset used in the analysis was constructed by combining several complementary UCR data sources and harmonizing them into a unified city-year panel.

The first component comes from The Marshall Project's cleaned version of the *Offenses Known and Clearances by Arrest* records (Dance, Meagher and Hopkins 2016, United States.

Federal Bureau of Investigation. 2022). This dataset is organized at the police-agency level, but as the majority of the police agencies chosen are municipal departments, for ease of phrasing the study refers to the sample as cities. For the purposes of the analysis, only the years 2001 to 2012 are retained, and to make the crime measures comparable across cities of different sizes, per-capita variables are constructed by dividing each crime count by the corresponding population.

The second component, the UCR *Property Stolen and Recovered* files (United States. Federal Bureau of Investigation. 2023) required more extensive construction. This dataset offers a more granular view of criminal activity by reporting the number of offenses in detailed subcategories as well as the monetary value of property stolen, and the value recovered. Each row corresponds to a reporting agency identified by its ORI code, along with administrative and geographic metadata such as agency name, FIPS codes, and the agency's postal address. The dataset covers a long historical period, with annual records available from 1960 up to 2024.

The first step in preparing the data was to select the subset corresponding to the relevant time range for this analysis, 2001 to 2012. To adapt the agency-level data to a city-level structure, the *agency_name* field is used as a proxy for the agency's city, as agency names typically correspond to the municipality in which the agency operates. It is, however, important to note that this constitutes an approximation for the purposes of the analysis.

The city-like component is extracted from each full agency name (e.g., "New York" from "New York State Police," "Los Angeles" from "Los Angeles State Police") and the cleaned string stored in a new variable, *city*. The fuzzy-matching function is then used to compare these extracted names to a list of 'target cities' (those appearing in the *Offenses Known and Clearances by Arrest* dataset). Extracted city names with a similarity score above a pre-specified threshold were retained, while all other observations were excluded. This process ensures that both datasets refer to a consistent set of U.S. cities, enabling accurate merging and analysis.

Once the relevant observations had been identified, the final step of the cleaning involved dropping unnecessary columns and aggregating data to the city-year level. The resulting city-year panel was merged with the *Offenses Known and Clearances by Arrest* dataset using a city-year key.

4.3.3. Variables

The dataset covers 46 major U.S. cities, over the years 2001 to 2013, and contains 552 annual observations with 105 variables. It records the year and city identifiers, along with detailed information on the rollout of Google Street View, including the specific year and month in which the service became available and a binary indicator capturing whether Street View was accessible in a given city-year. Annual population figures are included as well.

A first part of the dataset contains overall crime indicators, providing broad measures of public safety. These include total violent crimes, robberies, burglaries, larcenies/thefts, motor-vehicle thefts, and their corresponding per-capita measures (crimes per 100,000 residents). It further provides a rich breakdown of property and opportunity-driven offenses, including robbery subtypes (e.g., highway, bank, gas station, chain store, residential), burglary categories disaggregated by residential versus non-residential incidents and by time of day, and numerous larceny/theft subcategories such as shoplifting, theft from buildings or automobiles, bicycle theft, purse snatching, pickpocketing, and auto-parts theft. Motor-vehicle theft and recovery indicators are also reported.

Finally, the dataset includes several property-value variables, capturing both the value of stolen goods, reported for each offense category and in total, and the value of recovered property across the same set of categories.

4.3.4. Model Specification and Variable Transformation

A broad exploratory data analysis is conducted to examine the dataset's overall size, variable types, and initial observations, followed by a systematic inspection of missing values and summary statistics for all numeric variables. To evaluate the suitability of log-transforming variables, the distributions of selected crime variables are compared in both raw and log-transformed form.

The raw variables exhibit substantial right-skewness, with a small number of large cities generating extremely high crime volumes that dominate the distribution. This produces highly uneven scales and large disparities across cities, which obscure trend patterns. After applying a *log(1+x)* transformation, the distributions become far more symmetric, outliers are compressed, and the scales across cities become much more comparable. Owing to the large number of variables analyzed, **Figure 6** includes histograms for only a representative subset of outcomes.

4.4. Education

4.4.1. Data Sources

The education data used in this thesis are drawn from the National Center for Education Statistics (NCES), the primary federal source for comprehensive information on U.S. elementary and secondary schooling.

The core dataset is obtained from the Elementary/Secondary Information System (ElSi), an NCES web platform that provides direct access to annual indicators from the Common Core of Data (CCD) for public schools and from the Private School Survey (PSS) for private institutions (National Center for Education Statistics). ElSi allows users to generate customized tables and extract variables related to student enrollment, staffing, school resources, and district characteristics, offering a consistent and authoritative basis for analyzing educational patterns across cities. Because ElSi does not directly report city-level counts of schools, this variable was obtained separately from the NCES Public School Universe Survey (National Center for Education Statistics), a yearly census of all U.S. public schools.

By combining information from these complementary NCES sources, the education dataset captures both system-level characteristics and school-level infrastructure, enabling a comprehensive examination of how educational environments evolve over time.

4.4.2. Data Preprocessing

The construction of the education dataset involved several steps to harmonize and integrate the information into a consistent city-year panel. The core of the dataset was obtained through the web application Elementary/Secondary Information System (National Center for Education Statistics). To supplement these measures, the year-over-year enrollment growth rate was included, calculated by comparing the number of students enrolled in each city with its value from the previous year. The number of public schools operating in each city was then incorporated. This variable was derived from the NCES Public School Universe Survey (National Center for Education Statistics). For each year between 2000 and 2012, the corresponding Public School Universe files were downloaded and used to count the number of schools associated with each city. Aggregating these records yielded an annual school-count variable capturing changes in local educational infrastructure over time. This measure was then merged with the ElSi dataset using city and year identifiers, resulting in a unified education panel that combines enrolment, staffing, financial, and infrastructural indicators.

This merged dataset constitutes the basis for the education component of the empirical analysis.

4.4.3. Variables

The dataset covers 88 major U.S. cities, over the years from 2000 to 2011, yielding 1.048 observations and 15 variables. For each city-year, the dataset reports the state, the year, and detailed information on the rollout of Google Street View, including the year and month of introduction as well as an indicator signaling whether GSV was available in that particular year.

The dataset then provides a set of education-related variables, beginning with total students, the annual enrolment growth rate, the number of teachers, total staff positions, and the number of schools. Financial indicators come from the CCD LEA Finance (F-33) survey (National Center for Education Statistics) and include total revenue from federal, state, and local sources, as well as expenditures on public elementary and secondary education, facilities acquisition, construction, equipment, other programs, and interest on debt.

Additional educational variables include the dropout rate, defined as the number of grade dropouts relative to the enrollment base, and the pupil-teacher ratio, computed as total students divided by total teachers. Together, these variables offer a comprehensive annual portrait of school-system resources, financial conditions, and student outcomes across a wide set of U.S. cities during the period of Google Street View's national rollout.

4.4.4. Model Specification and Variable Transformation

The exploratory analysis of the education dataset begins with an examination of its structure, including the number of observations, variable types, and the completeness of key indicators. The distributions of core education outcomes, such as total enrollment, school counts, and expenditures, are assessed in both raw and log-transformed form.

The raw variables exhibit substantial right-skewness, with a small number of large school districts accounting for disproportionately high activity levels. This skewness produces uneven scales, wide dispersion, and obscured temporal patterns. To address these issues, a *log(1+x)* transformation is applied to all variables, excluding those that represent ratios or percentages (e.g., pupil-teacher ratio, dropout rate, enrollment growth rate) as well as variables that encode treatment status or timing.

After transformation and renaming of the variables, histograms of the logged series indicate more symmetric distributions and reduced influence of extreme outliers (Figure 15). These diagnostics support the use of log-transformed education variables in the empirical analysis.

5. Results

5.1. Empirical specification and outcome selection

A limited set of key results is emphasized because they best capture the mechanisms being tested and allow the findings across different outcome areas to be presented consistently. Urban growth is analyzed using the logarithm of the number of workers in mid-March and the population count, which represent economic and demographic development. Financial results are indicated by the logarithm of the average property price illustrating housing market trends. Tourism is evaluated based on the logarithm of the quantity of tourist sites and hotel occupancy percentages whereas population mobility is represented by the number of registered vehicles per capita. Crime trends are guided by the logarithm of the total theft value, violent and burglary crimes and educational resources are assessed using the natural logarithm of the count of schools and students. Collectively these metrics offer a perspective on the potential impact of the treatment, on local economic, social and infrastructure factors.

These variables are chosen as they effectively reflect the mechanisms through which Google Street View is anticipated to influence urban development and because they demonstrate the clearest and most consistent trends in the dataset. To prevent repeated analysis of results in various thematic sections each variable is linked to only one domain. Synthetic Difference-in-Differences (SDID) was explored as an additional estimator but ultimately discarded, as the implementation did not perform reliably with the available datasets.

5.2. Crime

This section presents the estimated effects of Google Street View introduction on crime outcomes, specifically log-transformed overall value of theft offenses, total number of violent crimes, and total number of burglary offenses.

5.2.1. Theft Value

Table 7 below shows that the Callaway-Sant'Anna estimator identifies a statistically significant increase of 0.213, which corresponds to a 21% rise in the value of theft following GSV introduction. The Sun-Abraham estimate is also positive but smaller and not statistically significant, while TWFE yields a negative and imprecise estimate. Pre-treatment averages for both CS and SA are close to zero, providing no evidence of trends before treatment. Dynamic effects reported in Table 30 confirm this pattern. Pre-treatment coefficients are statistically indistinguishable from zero and consistent with the formal parallel-trends tests in Table 31. Post-treatment, the Callaway-Sant'Anna estimates become larger and more precisely estimated: the effect rises to 0.371 at t + 1 (SE 0.1818, $p<0.05$) and remains substantial at 0.332 at t + 2 (SE 0.0880, $p<0.01$). The Sun-Abraham results remain statistically insignificant.

Table 1: Treatment Effects - Three DiD Estimators

Dependent variable: Log Value Total Thefts

	(1) CS	(2) SA	(3) TWFE
Overall ATT	0.2130***	0.1568	-0.1659
	(0.0770)	*(0.1250)*	*(0.1782)*
Pre-treatment (avg)	-0.0310	-0.3532	
	(0.1006)	*(0.2496)*	*Has no dynamic pre-trend*
Observations	*552*	*552*	*552*
Treated observations	*227*	*227*	*227*
Control observations	*325*	*325*	*325*
Units	*46*	*46*	*46*
Time periods	*12*	*12*	*12*

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. (1) CS; (2) Sun-Abraham; (3) TWFE.

Cohort-specific estimates in Table 32 show that the aggregate positive effect is not driven by any individual cohort, as none of them is significant.

Figure 1: Two-Way Comparison Log Value Total Thefts

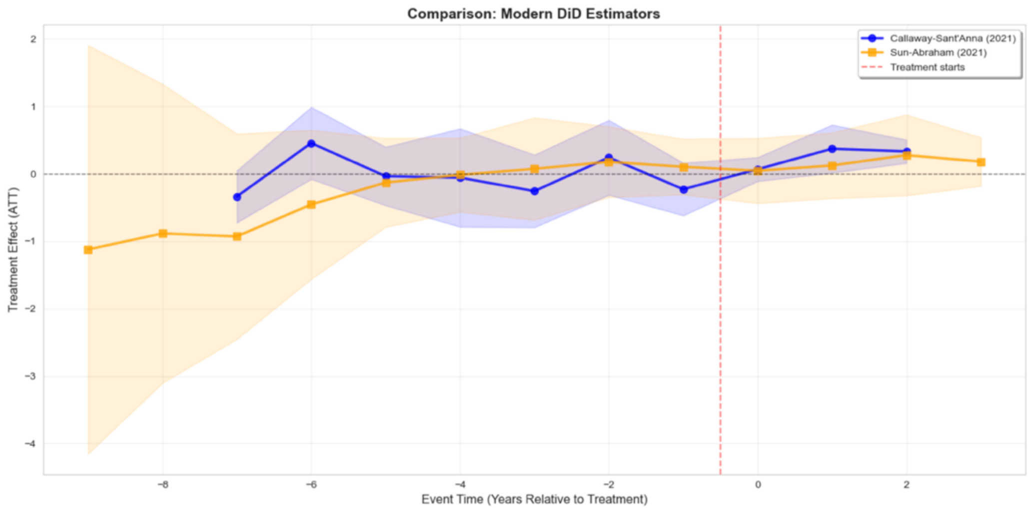


Figure 7 visually illustrates both modern DiD estimators' trajectories. There is no evidence of differential pre-trends, and the estimated treatment effects become positive and remain so for several years after GSV introduction.

5.2.2. Violent Crimes

Table 8 reports the average treatment effects. The Callaway-Sant'Anna estimator indicates a 3-4% decline in violent crime after GSV introduction. The Sun-Abraham estimator produces a positive and statistically significant effect, while TWFE remains small and imprecise. However, as Table 33 shows, only the Callaway-Sant'Anna specification satisfies the parallel trends assumption, whereas the Sun-Abraham estimator displays a significant upward pre-trend (0.0788, $p = 0.003$). Consequently, only the Callaway-Sant'Anna estimates can be interpreted as causal**.**

Table 2: Treatment Effects - Three DiD Estimators
Dependent variable: Log Violent Crimes

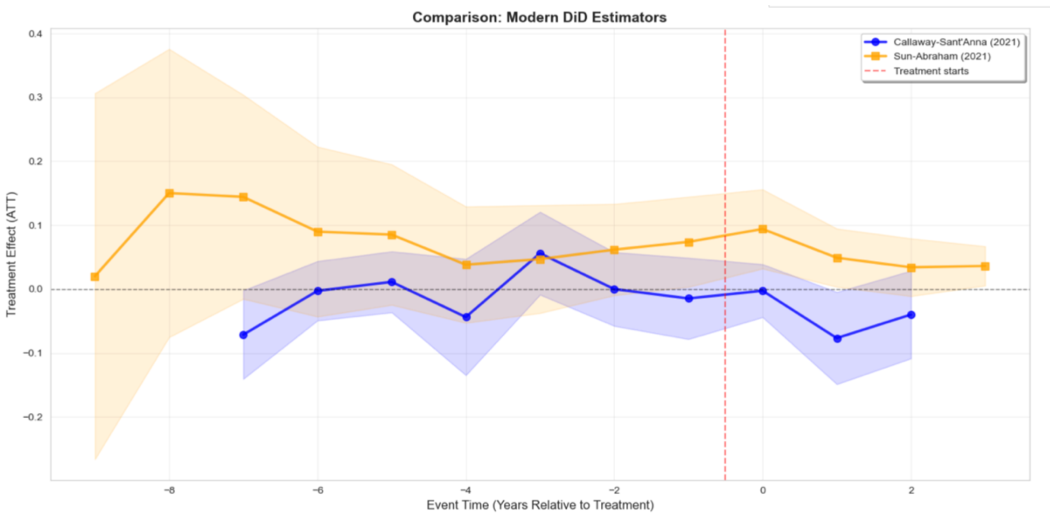
	(1) CS	(2) SA	(3) TWFE
Overall ATT	-0.0336*	0.0533***	0.0153
	(0.0172)	*(0.0120)*	*(0.0358)*
Pre-treatment (avg)	-0.0094	0.0788	

	(0.0124)	(0.0262)	Has no dynamic pre-trend
Observations	*552*	*552*	*552*
Treated observations	*227*	*227*	*227*
Control observations	*325*	*325*	*325*
Units	*46*	*46*	*46*
Time periods	*12*	*12*	*12*

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. (1) CS; (2) Sun-Abraham; (3) TWFE.

Dynamic patterns in Table 34 reinforce this distinction. The Callaway-Sant'Anna event-study coefficients show no significant movements before treatment and a modest but temporary decline after rollout, with a statistically significant reduction at $t + 1$. This effect fades by $t + 2$, and no sustained post-treatment impact is observed. In contrast, the Sun-Abraham series exhibits several significant coefficients, both before and after treatment, which indicates a violation of the parallel trends assumption and consequently non-credible treatment-effects. The Callaway-Sant'Anna trajectory in Figure 8 remains centered around zero both before and after treatment, while the Sun-Abraham trajectory rises steadily in the pre-treatment period and remains positive. This graphical evidence aligns with the formal pre-trend statistics in Table 33 and underscores the lack of estimator validity for Sun-Abraham in this context.

Figure 2: Two-Way Comparison Log Violent Crimes



Finally, Table 35 reports treatment effects by adoption cohort. All cohort-specific ATTs are small and statistically indistinguishable from zero.

5.2.3. Burglary Offenses

Table 3: Treatment Effects - Three DiD Estimators
Dependent variable: Log Total Burglary Offense

	(1) CS	(2) SA	(3) TWFE
Overall ATT	-0.0994*	0.3092**	-0.2423
	(0.0581)	*(0.1288)*	*(0.1918)*
Pre-treatment (avg)	-0.0440	-0.1644	
	(0.0941)	*(0.2316)*	*Has no dynamic pre-trend*
Observations	*552*	*552*	*552*
Treated observations	*227*	*227*	*227*
Control observations	*325*	*325*	*325*
Units	*46*	*46*	*46*
Time periods	*12*	*12*	*12*

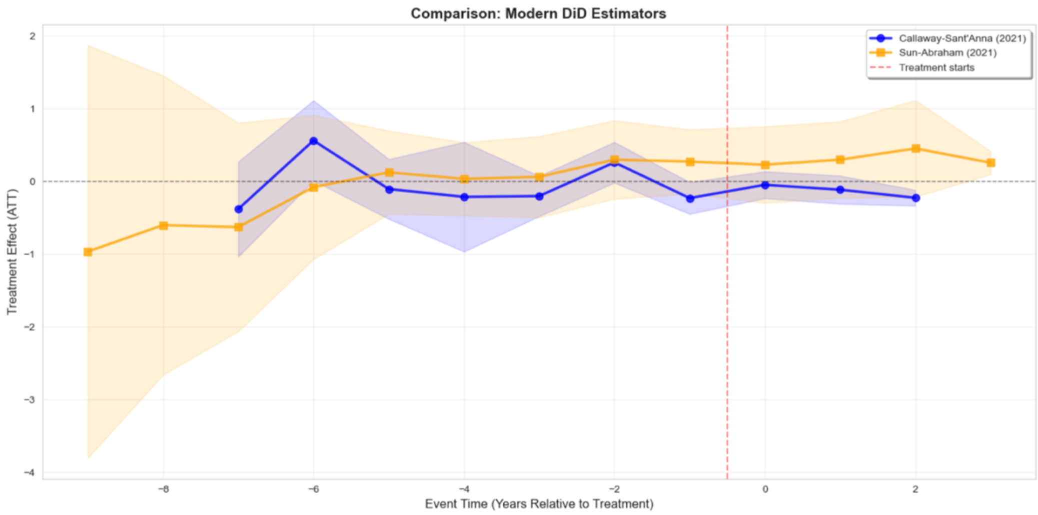
Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. (1) CS; (2) Sun-Abraham; (3) TWFE.

Table 9 above shows that the Callaway-Sant'Anna estimator identifies a negative and marginally significant ATT of -0.0994, implying a 9-10% decline in burglary after GSV introduction. By contrast, the Sun-Abraham estimate is positive and statistically significant, while the TWFE coefficient is negative but imprecise.

Pre-treatment averages in Table 36 are small and statistically insignificant for both estimators, indicating no systematic pre-treatment differences and supporting identification. Given its more stable weighting structure and smaller post-treatment magnitude, the CS estimator is treated as the most credible causal estimate.

Dynamic effects in Table 37 show some variability before treatment, but these irregularities average out and do not violate parallel trends. Figure 9 visually shows that the Callaway-Sant'Anna trajectory remains close to zero before treatment and shows a clear downward shift in the post-treatment period. The Sun-Abraham trajectory, by contrast, is consistently higher and more volatile. The comparison highlights the stability of the CS estimator and the fragility of the SA estimates in this setting.

Figure 3: Two-Way Comparison Log Total Burglary Offense



Cohort-specific results in Table 38 further support these findings: all cohort ATTs are small and statistically insignificant, indicating that the aggregate decline is not driven by any single adoption wave.

5.3. Education

This section presents the estimated effects of Google Street View introduction on education outcomes, specifically log-transformed number of schools and number of students.

5.3.1. Number of Schools

Table 10 reports the average treatment effects across estimators. The Callaway-Sant'Anna estimator identifies a small but statistically significant 3% rise in the number of schools following GSV introduction. The Sun-Abraham estimator, by contrast, yields a negative and marginally significant estimate, while the TWFE estimator produces a positive estimated effect of similar magnitude to CS.

Table 4: Treatment Effects - Three DiD Estimators
Dependent variable: Log Number of Schools

	(1) CS	(2) SA	(3) TWFE
Overall ATT	0.0292***	-0.1301*	0.0314**
	(0.0098)	*(0.0672)*	*(0.0133)*
Pre-treatment (avg)	0.0006	-0.1378	

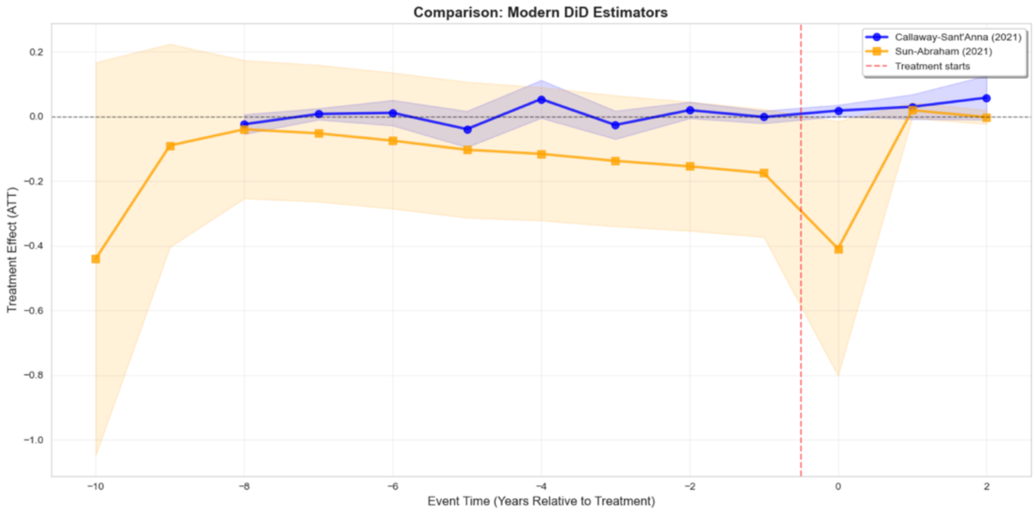
	(0.0071)	*(0.0459)*	*Has no dynamic pre-trend*
Observations	*1,048*	*1,048*	*1,048*
Treated observations	*339*	*339*	*339*
Control observations	*709*	*709*	*709*
Units	*88*	*88*	*88*
Time periods	*12*	*12*	*12*

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. (1) CS; (2) Sun-Abraham; (3) TWFE.

Table 39 sheds light on these discrepancies. The Callaway-Sant'Anna estimator exhibits a virtually zero pre-treatment mean effect, supporting the validity of its identifying assumptions. The Sun-Abraham estimator, however, displays a substantial and statistically significant negative pre-trend (-0.1378, p = 0.0027), suggesting that treated units were already on a downward trajectory before GSV rollout. As a result, only the Callaway-Sant'Anna estimates should be interpreted as credible in this setting, indicating a modest positive effect on the number of schools. Dynamic estimates in Table 40 further reinforce this conclusion. The Callaway-Sant'Anna model shows flat pre-treatment coefficients and small, positive post-treatment effects, with a statistically significant increase at $t = 0$ and a marginally significant rise at $t + 2$. The Sun-Abraham model, in contrast, exhibits pronounced negative movements in the pre-treatment period and a large negative estimate at $t = 0$, underscoring the estimator's violation of parallel trends, hence non-plausible treatment effects.

Figure 10 visually illustrates these dynamics. The Callaway-Sant'Anna trajectory remains tightly centered around zero throughout the pre-treatment period and shows a mild upward shift after rollout, with narrow confidence intervals indicating precision. Instead, the Sun-Abraham trajectory begins well below zero, trends upward toward treatment, and drops sharply again at $t = 0$, displaying instability and wide confidence intervals.

Figure 4: Two-Way Comparison Log Number of Schools



Cohort-specific results in Table 41 show a similarly consistent pattern. The 2007 cohort displays a statistically significant positive effect, while the 2008 and 2009 cohorts exhibit effects very close to zero and statistically indistinguishable from it.

5.3.2. Number of Students

Table 11 shows how all the estimators seem to yield statistically insignificant coefficients. These results suggest no measurable change in total enrollment following GSV introduction.

Table 5: Treatment Effects - Three DiD Estimators
Dependent variable: Log Total Students

	(1) CS	(2) SA	(3) TWFE
Overall ATT	0.0175	-0.0275	0.1043
	(0.0115)	*(0.0367)*	*(0.0742)*
Pre-treatment (avg)	-0.0015	-0.0115	
	(0.0105)	*(0.0285)*	*Has no dynamic pre-trend*
Observations	*1,048*	*1,048*	*1,048*
Treated observations	*339*	*339*	*339*
Control observations	*709*	*709*	*709*
Units	*88*	*88*	*88*
Time periods	*12*	*12*	*12*

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. (1) CS; (2) Sun-Abraham; (3) TWFE.

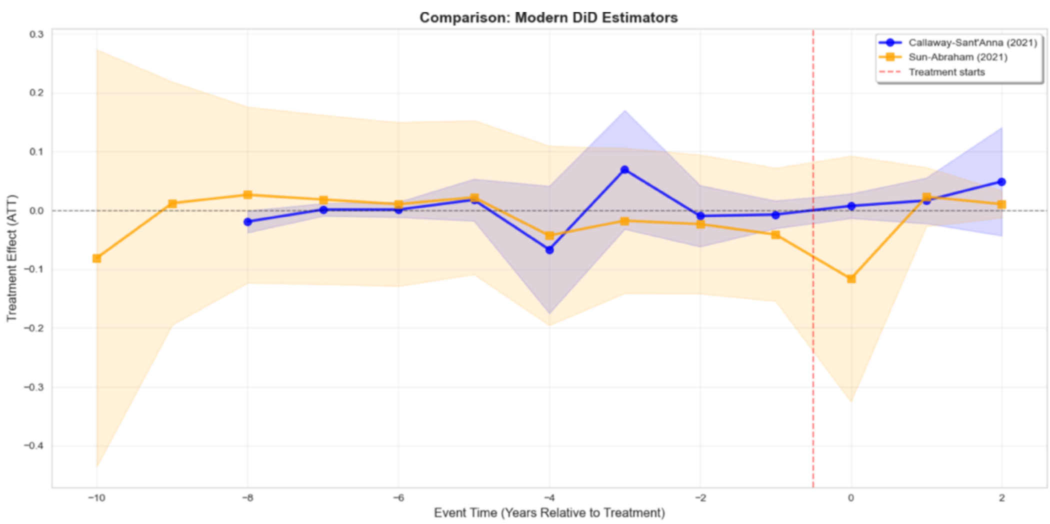
Table 42 shows that both modern DiD estimators satisfy the parallel trends assumption: pre-treatment averages are very close to zero and statistically insignificant, strengthening confidence in the absence of a true treatment effect for this outcome.

Dynamic estimates in Table 43 reinforce this conclusion. The Callaway-Sant'Anna event-study coefficients fluctuate around zero, with no statistically significant deviations before or after treatment. Sun-Abraham estimates are similarly small and unstable.

Finally, Table 44 reports cohort-specific effects. All estimates are small and statistically insignificant across the 2007, 2008, and 2009 adoption cohorts, further confirming the absence of heterogeneous responses across treatment waves.

Figure 11 visually compares the full dynamic. The Callaway-Sant'Anna path remains consistently close to zero, with tight confidence intervals. The Sun-Abraham path is more variable, especially in the pre-treatment period, but converges toward zero around treatment.

Figure 5: Two-Way Comparison Log Total Students



5.4. Robustness and alternative estimators

Three estimators are used throughout the analysis: TWFE, CS, and SA. This comparison is important given the staggered rollout of Google Street View and the potential biases of TWFE in the presence of heterogeneous treatment effects.

Overall, the Callaway-Sant'Anna estimator provides the most reliable results. For most outcomes, it satisfies the parallel trends assumption, with small and statistically insignificant pre-treatment effects and relatively flat pre-treatment event-study paths. The Sun-Abraham estimator, by contrast, often exhibits significant pre-treatment effects, particularly for population, tourism, mobility, violent crime, and education outcomes. These pre-trends limit the causal interpretation of SA estimates, which are therefore used mainly as robustness checks rather than as the primary source of inference.

TWFE estimates are generally smaller in magnitude and frequently closer to zero than those from the modern DiD estimators (Goodman-Bacon 2021). In several cases, they differ in sign from the CS estimates, consistent with recent methodological findings that TWFE can be misleading when treatment effects vary across cohorts and over time (Sun and Abraham 2021). Cohort-specific analyses further support the robustness of the main findings, as results are not driven by a single treatment wave but are broadly similar across adoption cohorts. Additional robustness checks using alternative outcomes are reported in the appendix and largely confirm the main patterns. Taken together, these checks indicate that while estimates vary across methods, the conclusions based on the Callaway-Sant'Anna estimator are the most credible and robust.

6. Discussion

6.1. Crime

Across the crime outcomes examined, the results reveal differentiated behavioral responses to the introduction of Google Street View, offering insights into how digital visibility may reshape both opportunity structures and offender decision-making.

Focusing first on the results deriving from the analysis on theft value, the evidence points to a clear and credible post-treatment increase. The Callaway-Sant'Anna estimator, which satisfies the fundamental parallel trends assumption, detects a statistically significant 21% rise in theft value following rollout, with event-study coefficients indicating that the effect strengthens one and two years after treatment and remains consistently positive across dynamic specifications. The Sun-Abraham estimates, while less precise, move in the same direction.

These findings support the hypothesis that Google Street View availability affects the total value of theft offenses in treated cities. Specifically, GSV may increase theft losses by reducing search costs and information frictions, and enabling offenders to remotely assess streets, access points and neighborhood layouts, thereby facilitating target selection without physical presence.

As for the analysis on violent crimes, only the Callaway-Sant'Anna specification satisfies validity checks, and it reveals a small, short-lived reduction which quickly dissipates.

This pattern aligns with the notion that violent crimes are less dependent on environmental reconnaissance and are therefore insensitive to improvements in street-level digital information. Burglary, however, constitutes the most unexpected finding. A priori, one might anticipate burglary to behave similarly to theft. A reasonable expectation is that GSV would *increase* burglary by enabling offenders to use virtual imagery to identify entry points or plan routes, mirroring the informational mechanisms that appear to increase theft. Yet the empirical evidence contradicts this expectation: the most credible estimator (Callaway-Sant'Anna) reveals a meaningful 9-10% overall decline in burglary, with dynamic results showing an especially pronounced reduction around two years after rollout. Several behavioral mechanisms may reconcile this negative effect with theoretical priors.

First, it is crucial to recognize a fundamental difference between theft and burglary. While theft crimes are *opportunistic*, burglary crimes are *invasive*, in that they require physical entry into private structures and involve higher legal and personal risk. This distinction implies greater sensitivity to perceived surveillance and guardianship. In this context, widespread public access to street-level imagery may heighten the perception that neighborhoods are “digitally exposed”, thereby deterring burglary attempts. On the other hand, opportunistic crimes such as theft exploit low-risk opportunities in public spaces, where the additional risk of “being seen” is relatively limited compared to the benefits of reduced search costs and information frictions.

Another point of view may be evaluated by considering the work of Van Daele et al. (2012). As previously stated, this study shows that burglars do use GSV when evaluating target suitability, and such information can refine their situational assessments, yet they rarely expand their geographic search patterns using GSV; instead, they continue to operate in familiar areas, meaning the platform provides informational support without altering broader spatial routines. This behavioral constraint provides a plausible explanation for the negative burglary effect observed in the results: if burglars rely primarily on local knowledge and do not expand to higher opportunity but unfamiliar areas using GSV, then the informational benefits they gain from the platform may be limited, while the increased visibility and perceived surveillance introduced by GSV could simultaneously heighten risk.

These results illustrate that GSV does not generate a uniform influence across crime types: while theft appears to increase as offenders exploit informational advantages, burglary decreases, likely due to its invasive nature and higher sensitivity to perceived surveillance and risk. Violent crimes, meanwhile, remain largely unaffected.

6.2. Education

Across the education outcomes examined, the empirical results provide a nuanced assessment of whether Google Street View affects educational infrastructure and educational participation through distinct channels, producing asymmetric responses on the supply and demand sides of local education systems. While the availability of GSV is associated with modest changes in the provision of schools, it does not appear to alter student enrollment patterns, suggesting that digital visibility primarily influences institutional investment decisions rather than household educational choices.

Beginning with the number of schools as a key indicator of local educational infrastructure, the Callaway-Sant'Anna estimator, which is the only specification satisfying the necessary identification conditions, reveals a modest but statistically significant increase of approximately 3% following GSV introduction, with flat pre-treatment dynamics and small, consistently positive post-treatment movements that become more pronounced around two years after rollout. This pattern suggests that GSV exposure may subtly improve the perceived attractiveness or functional accessibility of local areas by enhancing spatial transparency, reducing informational frictions about neighborhood characteristics, and potentially encouraging educational institutions or local authorities to invest in settings that appear better documented. The finding aligns with broader theories in urban sociology and environmental perception, which emphasize that public representations of space, including digital mapping, can influence institutional behavior and community evaluations of neighborhood quality (Burgess, et al. 2015, Zhang and Dong 2018, Rundle, et al. 2011, Odgers, et al. 2012).

In contrast, the results for student enrollment point to no demand-side response. Across all estimators, including the valid Callaway-Sant'Anna specification, the effects on total enrollment are consistently small, tightly centered around zero, and never statistically significant, with dynamic profiles showing no meaningful deviations before or after treatment. This absence of enrollment effects indicates that even if GSV modifies perceptions of urban environments, such changes do not translate into shifts in family schooling decisions or student distribution across cities, likely because enrollment decisions are driven by different structural factors such as residential location and long-term demographic trends rather than short-run improvements in publicly available spatial information.

Taken together, these findings provide partial support for the education hypothesis. Google Street View appears to affect the supply side of education by modestly increasing the number of schools, likely through reduced information and coordination costs for institutional decision-makers. However, it does not meaningfully influence the demand side, as households' schooling choices remain largely unaffected. Overall, the results suggest that digital representations of space are more consequential for infrastructural and investment-oriented decisions than for individual educational behavior.

7. Conclusion

7.1. Overall Contribution

This thesis asks whether the rollout of Google Street View has a causal impact on urban, economic, and social outcomes in U.S. cities. Using modern staggered Difference-in-Differences methods, the analysis shows that GSV clearly influences outcomes that are closely tied to perception and information, most notably housing markets, where visual visibility reshapes how neighborhoods are evaluated.

By contrast, GSV appears to matter less for slow-moving structural outcomes such as population size and employment levels, which show small and often negligible responses. Across domains, estimated effects are generally modest in magnitude and heterogeneous across cities and cohorts, suggesting that GSV functions primarily as an informational shock rather than a direct driver of large-scale urban change. Overall, the findings highlight digital visibility as a relevant but limited force: it refines decisions and perceptions, especially in domains sensitive to visual cues, without fundamentally reshaping underlying urban trajectories.

7.2. Domain-Specific Conclusions

7.2.1. Crime

The crime analyses show that Google Street View produces heterogeneous effects across offense categories, highlighting that digital visibility does not uniformly deter or facilitate crime. Theft consistently increases after GSV rollout, suggesting that offenders may exploit publicly available imagery to improve target assessment or navigation in familiar areas. Violent crime, by contrast, remains essentially unchanged, aside from a short-lived decline, reflecting its limited dependence on environmental planning. Burglary presents the most informative contrast. Despite being a planned property crime, burglary declines after GSV introduction, underscoring the distinction between opportunistic and invasive offenses. Unlike theft, burglary requires physical entry into private spaces and prolonged exposure, making offenders more sensitive to perceived surveillance and risk. Although research indicates that burglars may use GSV to assess targets, its limited role in expanding spatial activity, combined with heightened digital visibility, appears to shift the balance toward deterrence.

Taken together, the findings provide only partial support for the hypothesis that GSV's crime-reducing effect should be stronger for property- and opportunity-driven offenses than for violent crimes, because of the fundamental difference between the nature of these types of crimes. While burglary declines, theft rises, illustrating that GSV acts as a dual-use technology that simultaneously alters offender capabilities and perceived risks in ways that generate divergent behavioral responses.

7.2.2. Education

The education results indicate that GSV influences local educational infrastructure more than household schooling decisions. The number of schools increases modestly and reliably after GSV introduction, suggesting that enhanced digital visibility may improve neighborhood attractiveness, strengthen public scrutiny, or make certain areas appear more suitable for institutional investment. In contrast, student enrollment shows no measurable response, remaining stable across all estimators and dynamic patterns. This asymmetry implies that while institutions may adjust capacity or administrative decisions when neighborhoods become more visible and legible, families do not revise their educational choices in ways detectable at the city level. As a result, the central hypothesis that GSV modifies educational patterns by shaping perceptions of public space, receives only partial support: GSV appears to influence the supply of educational infrastructure but not the demand reflected in enrollment. Together, these findings underscore the selective and context-dependent nature of digital spatial technologies in shaping urban social outcomes.

8. Limitations & Future Research

Despite providing new evidence on the role of digital visibility in shaping urban outcomes, this study is subject to several limitations that should be acknowledged when interpreting the results. These limitations also point to promising directions for future research.

8.1. Limitations

A first limitation concerns Google Street View coverage and representativeness. Although GSV provides detailed street-level imagery, its spatial and temporal coverage is not uniform. Prior research shows that street-view imagery may underrepresent peripheral, informal, or rapidly changing areas, potentially biasing digital visibility toward well-documented neighborhoods (Biljecki and Ito 2021, Wang 2024). As a result, GSV may disproportionately enhance the visibility of already advantaged areas, reinforcing existing spatial inequalities and limiting the generalizability of the estimated effects.

Second, and more fundamentally, this study evaluates a hyper-local intervention using city-level outcome data. GSV operates at the scale of streets and neighborhoods, influencing perceptions of safety, attractiveness, accessibility, and surveillance in very localized areas. By contrast, outcomes such as total population, unemployment rates, or average housing prices are measured at the city-year level. This mismatch in spatial scale likely generates attenuation bias, as any localized effects are averaged over large and heterogeneous urban areas. In practice, GSV's impact is likely concentrated in specific neighborhoods, such as gentrifying districts, tourist corridors, or areas undergoing redevelopment, while much of the city remains unaffected. Aggregation therefore dilutes the signal, making it unlikely that street-level imagery would meaningfully shift city-wide population or labor-market indicators, even if neighborhood-level effects are substantial.

Third, the timing of GSV rollout (2007-2010) overlaps with the Great Recession, a major macroeconomic shock that directly affected housing markets, employment, urban development, and municipal finances. This overlap complicates causal interpretation, particularly for outcomes related to urban expansion and financial performance. Although staggered adoption and modern DiD estimators reduce bias from heterogeneous treatment timing, the crisis likely overshadowed GSV's informational effects in many cities. This helps explain the noisy and mixed results observed for outcomes such as home prices and employment, as well as why TWFE and modern estimators sometimes yield different magnitudes or levels of statistical significance. These estimators differ in how they weight time shocks and early treated units, which becomes especially consequential during periods of large aggregate volatility.

Fourth, identification challenges inherent to staggered treatment designs remain relevant. While this research relies primarily on Callaway-Sant'Anna and Sun-Abraham estimators to address known biases in TWFE models (Goodman-Bacon 2021, Sun and

Abraham 2021) some outcomes exhibit sensitivity to estimator choice or evidence of pre-treatment deviations. In these cases, results should be interpreted as suggestive rather than strictly causal, particularly when estimated effects are small relative to underlying outcome variability.

Fifth, the reliance on city-level aggregation masks within-city heterogeneity. Many of the mechanisms through which GSV may operate, such as changes in perceived safety, neighborhood desirability, or informal surveillance, are inherently local. Aggregation may therefore obscure meaningful variation across neighborhoods, especially for outcomes like crime, education, and housing markets, where localized dynamics are critical.

Finally, the analysis focuses on medium-run effects, constrained by data availability. Longer-term impacts on slow-moving outcomes, such as population composition, educational choices, or urban form, may unfold over longer horizons and are not fully captured in the current framework.

8.2. Future Research

These limitations point to several avenues for future research. First, studies using finer spatial resolution, such as neighborhood-level housing transactions or crime incidents, could better capture the mechanisms through which street-level imagery affects behavior. Second, future work could examine GSV updates and image refresh cycles, treating digital visibility as an evolving rather than one-time intervention. Third, cross-country analyses could test whether the effects identified here generalize beyond the U.S. context. Fourth, combining rollout timing with computer-vision-based measures extracted directly from GSV images would allow researchers to study how specific visual features interact with digital visibility. Finally, the heterogeneous crime results suggest the value of research that more directly examines behavioral responses by offenders and institutions, using experimental or qualitative approaches.

Bibliography

Aboalganam, Khaled M., Sakher Faisal AlFraihat, and Saeed Tarabieh. 2025. “The Impact of User-Generated Content on Tourist Visit Intentions: The Mediating Role of Destination Imagery.” *Administrative Sciences* 15 (4). https://doi.org/10.3390/admsci15040117.

AirROI. 2025. *Orlando Airbnb Market Analysis 2025: Short Term Rental Data & Vacation Rental Statistics in Florida, United States.* https://www.airroi.com/report/world/united-states/florida/orlando.

An, Sihyun, Hanwool Jang, Hwahwan Kim, Yena Song, and Kwangwon Ahn. 2023. “Assessment of Street-Level Greenness and Its Association with Housing Prices in a Metropolitan Area.” *Scientific Reports* 13.

Ayoola, Ayobami B., Oluwole A. Daramola, and Adedotun O. Ogunba. 2023. “Determining Residential Location Choice along the Coastline in Victoria Island, Nigeria Using a Factor Analytical Approach.” *Buildings* 13 (6).

Biljecki, Filip, and Koichi Ito. 2021. “Street view imagery in urban analytics and GIS: A review.” *Landscape and Urban Planning* 215. https://www.sciencedirect.com/science/article/pii/S0169204621001808.

Blanding, Michael, and Scott Duke Kominers. 2017. “Researchers Use Google Street View to See the Future of Cities.” *Harvard Business School.* 16 August. https://www.library.hbs.edu/working-knowledge/researchers-use-google-street-view-to-see-the-future-of-cities.

Bureau of Transportation Statistics. n.d. *Bureau of Transportation Statistics.* https://www.transtats.bts.gov/airports.asp?20=E.

Burgess, Simon, Ellen Greaves, Anna Vignoles, and Deborah Wilson. 2015. “What Parents Want: School Preferences and School Choice.” *The Economic Journal* 125 (587): 1262–1289. https://doi.org/10.1111/ecoj.12153.

Chainey, Spencer, Lisa Tompson, and Sebastian Uhlig. 2008. “The Utility of Hotspot Mapping for Predicting Spatial Patterns of Crime.” *Security Journal* 21: 4-28.

Curtis, Jacqueline W., Andrew Curtis, Jennifer Mapes, Andrea B. Szell, and Adam. Cinderich. 2013. “Using google street view for systematic observation of the built environment: analysis of spatio-temporal instability of imagery dates.” *International Journal of Health Geographics* 12.

Dance, Gabriel, Tom Meagher, and Emily Hopkins. 2016. “Crime in Context.” *The Marshall Project.* https://www.perplexity.ai/search/can-you-tell-me-if-this-is-a-g-kFJs23x6SSCATiJXRtyjIg.

Europol. 2017. “Crime in the age of technology - Europol’s Serious and Organised Crime Threat Assessment.”

Ewing Marion Kauffman Foundation. n.d. *Entrepreneurial Jobs Indicators.* https://indicators.kauffman.org/data-tables/jobs/msa/al/.

Federal Aviation Administration. n.d. *Air Traffic Activity Data System (ATADS) - Airport Operations.* https://www.aspm.faa.gov/opsnet/sys/airport.asp.

Federal Reserve Bank of St. Louis. n.d. *Federal Reserve Bank of St. Louis.* https://fred.stlouisfed.org/.

Goodman-Bacon, Andrew. 2021. “Difference-in-differences With Variation in Treatment Timing.” *ScienceDirect.* 20 October. https://www.sciencedirect.com/science/article/abs/pii/S0304407621001445.

Huber, Franz, Alan Ponce, Francesco Rentocchini, and Thomas Wainwright. 2022. “The wealth of (Open Data) nations? Open government data, country-level institutions and entrepreneurial activity.” *Industry and Innovation* 29 (8): 992–1023. https://doi.org/10.1080/13662716.2022.2109455.

HVS. n.d. *HVS Central Florida 2020 State of the Hotel Market.* https://www.hvs.com/article/8697-HVS-Central-Florida-2020-State-of-the-hotel-market.

Las Vegas Convention and Visitors Authority. n.d. *About the Las Vegas Convention and Visitors Authority.* https://www.lvcva.com/.

Law, Stephen, Brooks Paige, and Chris Russell. 2019. "Take a Look Around: Using Street View and Satellite Images to Estimate House Prices." *ACM Transactions on Intelligent Systems and Technology* 10 (5): 1-19. https://doi.org/10.1145/3342240.

Li, Yonghao, Jialin Lu, Yuan Meng, Yiwen Luo, and Juan Ren. 2025. “Exploring Urban Spatial Quality Through Street View Imagery and Human Perception Analysis.” *Buildings* 15 (17). https://www.mdpi.com/2075-5309/15/17/3116.

Macrotrends. n.d. *Macrotrends - The Premier Research Platform for Long Term Investors.* https://www.macrotrends.net/.

Marriott International. n.d. *Marriott International Reports Third Quarter 2010 Results.* https://marriott.gcs-web.com/news-releases/news-release-details/marriott-international-reports-third-quarter-2010-results.

Mobasheri, Amin, Francesco Pirotti, and Giorgio Agugiaro. 2020. “Open-source geospatial tools and technologies for urban and environmental studies.” *Open geospatial data, Software and Standards* 5. https://link.springer.com/article/10.1186/s40965-020-00078-2.

Mohagegh, Farhad, Aditia Sobarna, and Alfia Zahraputeri. 2022. "Gaining Loyalty Intention in Virtual Reality Tourism: A Lesson from US Tourists." *International Journal of Applied Business Research* 4: 1-15.

National Cancer Institute. n.d. *Download U.S. County Population Data - 1969-2023.* https://seer.cancer.gov/popdata/download.html.

National Center for Education Statistics. n.d. *Elementary/Secondary Information System (ElSi) Table Generator.* https://nces.ed.gov/ccd/elsi/tablegenerator.aspx.

National Center for Education Statistics. n.d. *The Common Core of Data (CCD).* https://nces.ed.gov/ccd/.

New York City Tourism + Conventions. n.d. *New York City Tourism + Conventions: Official Guide to NYC.* https://www.nycgo.com/.

Nguyen, Quynh C., Sahil Khanna, Pallavi Dwivedi, Dina Huang, Yuru Huang, Tolga Tasdizen, Kimberly D. Brunisholz, et al. 2019. "Using Google Street View to examine associations between built environment characteristics and U.S. health outcomes." *Preventive Medicine Reports* 14.

Nguyen, Sinh Hoang. 2025. "Leveraging Virtual Reality Experiences to Shape Tourists' Behavioral Intentions: The Mediating Roles of Enjoyment and Immersion." *Journal of Zoological and Botanical Gardens* 6 (2).

Odgers, Candice L., Avshalom Caspi, Christopher J. Bates, Robert J. Sampson, and Terrie E. Moffitt. 2012. "Systematic social observation of children's neighborhoods using Google Street View: a reliable and cost-effective method." *The Journal of Child Psychology and Psychiatry* 53 (10): 1009-1017.

Rundle, Andrew G., Michael D. M. Bader, Caroline A. Richards, Kathryn M. Neckerman, and Julien O. Teitler. 2011. "Using Google Street View to audit neighborhood environments." *American Journal of Preventive Medicine* 40 (1): 94-100.

Sayfuddin, A. T. M., and Yong Chen. 2021. "The Signaling and Reputational Effects of Customer Ratings on Hotel Revenues: Evidence from TripAdvisor." *International Journal of Hospitality Management* 99.

Stecuła, Kinga, and Mateusz. Naramski. 2025. "Virtual Reality as a Green Tourism Alternative: Social Acceptance and Perception." *Sustainability* 17.

Suel, Esra. 2019. "AI and Google street view images help monitor living conditions in cities." *Pathways to Equitable Healthy Cities.* 24 June. https://equitablehealthycities.org/blog/keep-your-eyes-on-the-street-ai-and-google-street-view-images-help-monitor-living-conditions-in-cities/.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating Dynamic Treatment Effects in Event Studies With Heterogeneous Treatment Effects." *ScienceDirect.* 20 October. https://www.sciencedirect.com/science/article/abs/pii/S030440762030378X.

Tu, Li, Xiao Jiang, Yixing Guo, and Qi Qin. 2025. "Effect of Visual Quality of Street Space on Tourists' Stay Willingness in Traditional Villages—Empirical Evidence from Huangcun Village Based on Street View Images and Machine Learning." *Land* 14 (8).

UNESCO International Institute for Educational Planning. n.d. "Geospatial data in educational planning and management." *International Institute for Educational Planning (IIEP-UNESCO).* https://www.iiep.unesco.org/en/geo.

United States. Federal Bureau of Investigation. 2022. "Uniform Crime Reporting Program Data: Offenses Known and Clearances by Arrest." *Inter-university Consortium for Political and Social Research.* https://doi.org/10.3886/ICPSR39066.v1.

United States. Federal Bureau of Investigation. 2023. "Uniform Crime Reporting Program Data: Property Stolen and Recovered." *Inter-university Consortium for Political and Social Research.* https://doi.org/10.3886/ICPSR38793.v1.

United States Bureau of Economic Analysis. n.d. *Personal Income by State.* https://www.bea.gov/data/income-saving/personal-income-by-state.

United States Bureau of Economics Analysis. n.d. *GDP by County, Metro, and Other Areas.* https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas.

United States Bureau of Labor Statistics. n.d. *State and Metro Area Employment, Hours, & Earnings.* https://www.bls.gov/sae/.

United States Census Bureau. n.d. *Census Datasets.* https://www.census.gov/data/datasets.html.

United States Census Bureau. n.d. *County Business Patterns: 2011.* https://www.census.gov/data/datasets/2011/econ/cbp/2011-cbp.html.

United States Census Bureau. n.d. *County Business Patterns Tables.* https://www.census.gov/programs-surveys/cbp/data/tables.html.

United States Census Bureau. n.d. *Small Area Health Insurance Estimates (SAHIE) Program.* https://www.census.gov/programs-surveys/sahie.html.

United States Census Bureau. n.d. *Small Area Income and Poverty Estimates (SAIPE) Program.* https://www.census.gov/programs-surveys/saipe.html.

Van Daele, Stijn, Marlijn Peeters, Christophe Vandeviver, Efien Ledure, and Tom. Vander Beken. 2012. "Technische hulpmiddelen en doelwitselectie bij woninginbraak: een experimenteel onderzoek naar de invloed van Google Maps en Google Street View." *TIJDSCHRIFT VOOR CRIMINOLOGIE* 54 (4): 362-373. http://hdl.handle.net/1854/LU-2112311.

Vandeviver, Christophe. 2014. "Applying Google Maps and Google Street View in criminological research." *Crime Science* 3. https://doi.org/10.1186/s40163-014-0013-2.

Visit Orlando. n.d. *Visit Orlando.* https://www.visitorlando.com/.

Visit Orlando. n.d. *Data and Trends.* https://www.visitorlando.org/about/resources/data-trends/.

Visit Seattle. n.d. *Visit Seattle Washington: Travel & Tourism Official Site.* https://visitseattle.org/.

Wang, Guan-Yuan. 2024. "Integrating Street Views, Satellite Imageries and Remote Sensing Data Into Economics and the Social Sciences." *Social Science Computer Review* 42 (1): 326-351.

Wikipedia. n.d. *Google Street View in the United States.* https://en.wikipedia.org/wiki/Google_Street_View_in_the_United_States.

Wilkins, Emily J., Spencer A. Wood, and Jordan W. Smith. 2021. "Uses and Limitations of Social Media to Inform Visitor Use Management in Parks and Protected Areas: A Systematic Review." *Environmental Management* 67: 120-132. https://doi.org/10.1007/s00267-020-01373-7.

Wirtz, Bernd W., Jan C. Weyerer, Marcel Becker, and Wilhelm M. Müller. 2022. "Open government data: A systematic literature review of empirical research." *Electronic Markets* 32: 2381–2404. https://link.springer.com/article/10.1007/s12525-022-00582-8.

Wood, Spencer A., Anne D. Guerry, Jessica M. Silver, and Martin. Lacayo. 2013. "Using social media to quantify nature-based tourism and recreation." *Scientific Reports* 3 (2976).

Wood, Spencer A., Samantha G. Winder, Emilia H. Lia, Eric M. White, Christian S. L. Crowley, and Adam A. Milnor. 2020. "Next-generation visitation models using social media to estimate recreation on public lands." 22 September. https://doi.org/10.1038/s41598-020-70829-x.

Wu, Huayi, Zhipeng Gui, and Zelong Yang. 2020. "Geospatial big data for urban planning and urban management." *Geo-Spatial Information Science* 23 (4): 273–274. https://doi.org/10.1080/10095020.2020.1854981.

Xu, Xiang, Waishan Qiu, Wenjing Li, Xun Liu, Ziye Zhang, Xiaojiang Li, and Dan. Luo. 2022. "Associations between Street-View Perceptions and Housing Prices: Subjective vs. Objective Measures Using Computer Vision and Machine Learning Techniques." *Remote Sensing.*

Ye, Yu, Hanting Xie, Jia Fang, Hetao Jiang, and De Wang. 2019. "Daily Accessed Street Greenery and Housing Price: Measuring Economic Performance of Human-Scale Streetscapes via New Urban Data." *Sustainability* 11 (6).

Zhang, Yonglin, and Rencai Dong. 2018. "Impacts of Street-Visible Greenery on Housing Prices: Evidence from a Hedonic Price Model and a Massive Street View Image

Dataset in Beijing." *ISPRS International Journal of Geo-Information* 7 (3). https://doi.org/10.3390/ijgi7030104.

Zillow. n.d. *Housing Data.* https://www.zillow.com/research/data/.

Appendix

Figure 6: Histograms of Log-Transformed Crime Variables

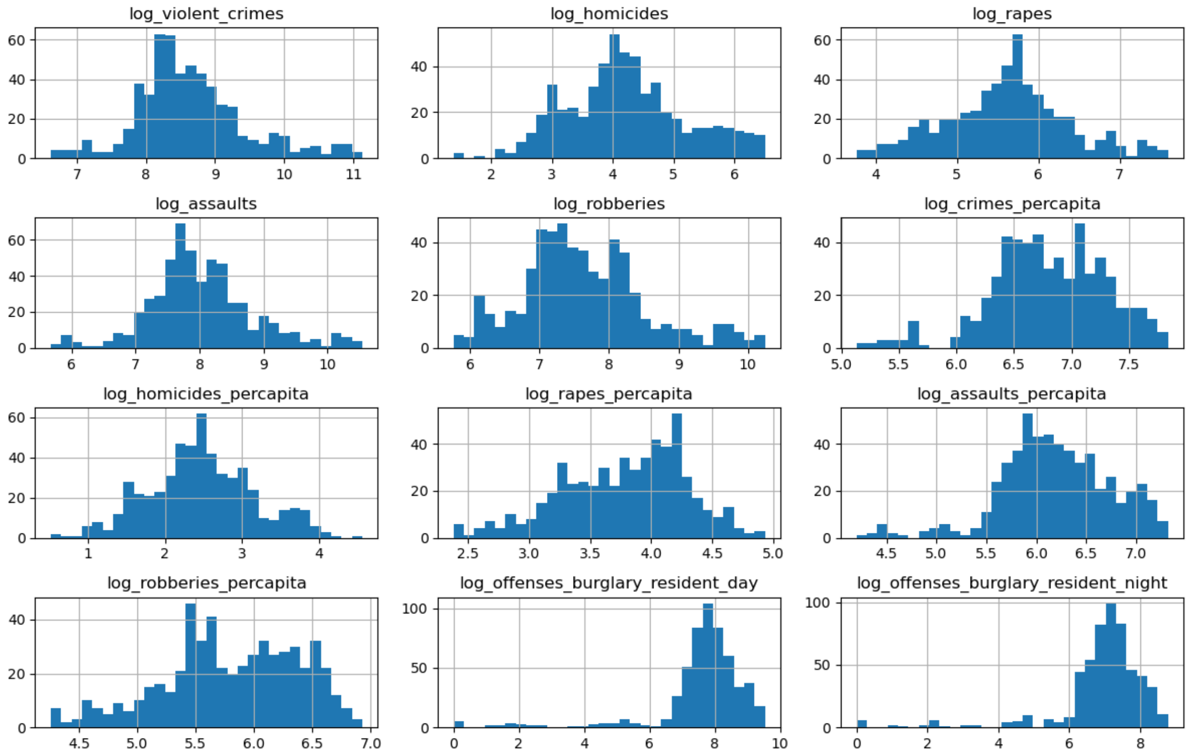


Figure 7: Histograms of Log-Transformed Education Variables

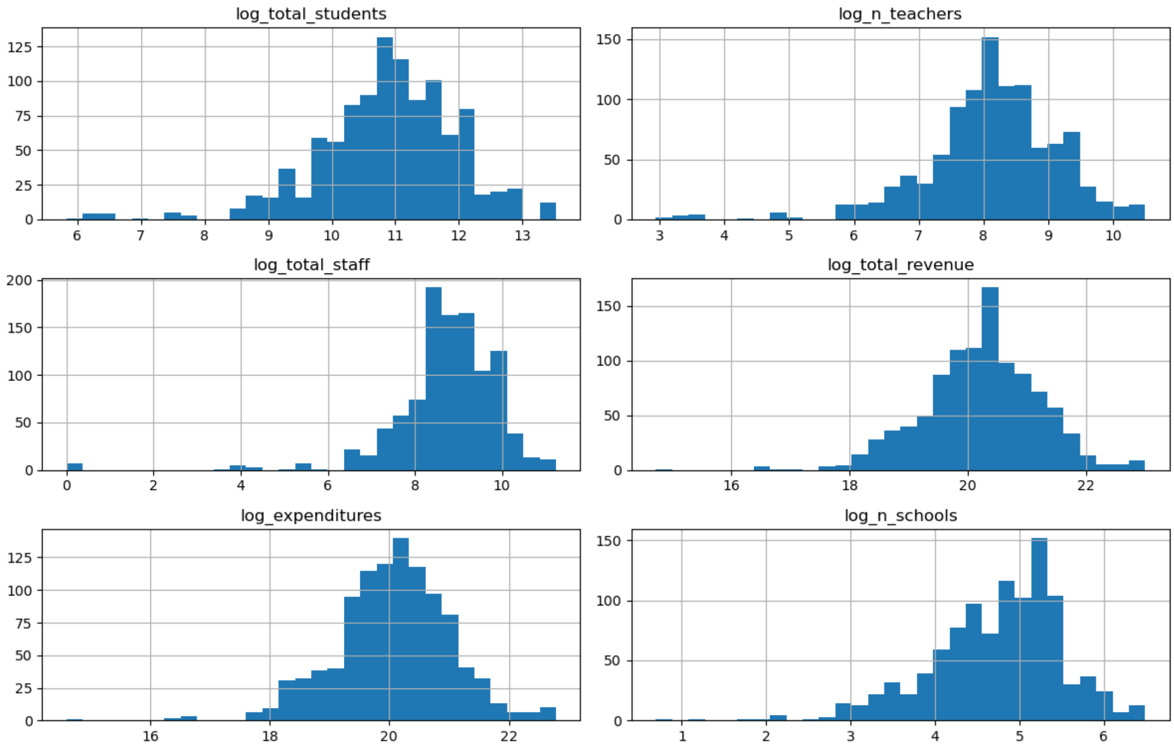


Table 6: Event Study Estimates - Selected Event Times

Dependent variable: Log Value Total Thefts

Period	(1) CS	(2) SA
Treatment - 2	0.2422	0.1777
	(0.2831)	*(0.2674)*
Treatment - 1	-0.2288	0.1044
	(0.1990)	*(0.2104)*
Treatment (t = 0)	0.0677	0.0455
	(0.0902)	*(0.2461)*
Treatment + 1	0.3712**	0.1241
	(0.1818)	*(0.2486)*
Treatment + 2	0.3323***	0.2769
	(0.0880)	*(0.3059)*
Treatment + 3		0.1808
		(0.1843)
Observations	552	552
Event times shown	6	6

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. (1) Callaway-Sant'Anna (2021); (2) Sun-Abraham (2021).

Table 7: Pre-Treatment Parallel Trends Test

Dependent variable: Log Value Total Thefts

Method	Mean Pre-Treatment Effect	SE	p-value	N periods
Callaway-Sant'Anna	-0.0310	0.1006	0.7579	7
Sun-Abraham	-0.3532	0.2496	0.1572	9

Note: Large p-values (> 0.05) support the parallel trends assumption. Mean pre-treatment effects near zero indicate no evidence of pre-trends.

Table 8: Treatment Effect Heterogeneity by Cohort

Estimator: Callaway-Sant'Anna (2021)

Cohort	**ATT (with SE)**	**Units**	**Post-Treatment Periods**
2007	-0.0472 (0.1653)	5	6
2008	0.0977 (0.1369)	34	5
2009	0.0551 (0.1277)	6	4

Note: ATT is the average treatment effect for units first treated in that cohort. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 9: Pre-Treatment Parallel Trends Test

Method	Mean Pre-Treatment Effect	SE	p-value	N periods
Callaway-Sant'Anna	-0.0094	0.0124	0.4498	7
Sun-Abraham	0.0788	0.0262	0.0026	9

Note: Large p-values (> 0.05) support the parallel trends assumption. Mean pre-treatment effects near zero indicate no evidence of pre-trends. Standard errors in parentheses.

Table 10: Event Study Estimates - Selected Event Times

Dependent variable: Log Violent Crimes

Period	(1) CS	(2) SA
Treatment - 2	-0.0001	0.0616*
	(0.0294)	*(0.0365)*
Treatment - 1	-0.0147	0.0738**
	(0.0325)	*(0.0360)*
Treatment (t = 0)	-0.0026	0.0939***
	(0.0212)	*(0.0316)*
Treatment + 1	-0.0768**	0.0490**
	(0.0368)	*(0.0233)*
Treatment + 2	-0.0400	0.0340
	(0.0350)	*(0.0231)*
Treatment + 3		0.0361**
		(0.0158)
Observations	552	552
Event times shown	6	6

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. (1) Callaway-Sant'Anna (2021); (2) Sun-Abraham (2021).

Table 11: Treatment Effect Heterogeneity by Cohort

Estimator: Callaway-Sant'Anna (2021)

Cohort	ATT (with SE)	Units	Post-Treatment Periods
2007	0.0022 (0.0174)	5	6
2008	-0.0143 (0.0155)	34	5
2009	-0.0195 (0.0221)	6	4

Note: ATT is the average treatment effect for units first treated in that cohort. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 12: Pre-Treatment Parallel Trends Test

Method	Mean Pre-Treatment Effect	SE	p-value	N periods
Callaway-Sant'Anna	-0.0440	0.0941	0.6397	7
Sun-Abraham	-0.1644	0.2316	0.4776	9

Note: Large p-values (> 0.05) support the parallel trends assumption. Mean pre-treatment effects near zero indicate no evidence of pre-trends. Standard errors in parentheses.

Table 13: Event Study Estimates - Selected Event Times
Dependent variable: Log Total Burglary Offense

Period	(1) CS	(2) SA
Treatment - 2	0.2609*	0.2987
	(0.1421)	*(0.2756)*
Treatment - 1	-0.2298**	0.2723
	(0.1111)	*(0.2253)*
Treatment (t = 0)	-0.0473	0.2297
	(0.0942)	*(0.2682)*
Treatment + 1	-0.1146	0.2984
	(0.0981)	*(0.2679)*
Treatment + 2	-0.2255***	0.4520
	(0.0553)	*(0.3392)*
Treatment + 3		0.2569***
		(0.0813)
Observations	552	552
Event times shown	6	6

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. (1) Callaway-Sant'Anna (2021); (2) Sun-Abraham (2021).

Table 14: Treatment Effect Heterogeneity by Cohort

Estimator: Callaway-Sant'Anna (2021)

Cohort	ATT (with SE)	Units	Post-Treatment Periods
2007	-0.2048 (0.1517)	5	6
2008	0.0210 (0.1018)	34	5
2009	0.0186 (0.0972)	6	4

Note: ATT is the average treatment effect for units first treated in that cohort. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 15: Pre-Treatment Parallel Trends Test

Method	Mean Pre-Treatment Effect	SE	p-value	N periods
Callaway-Sant'Anna	0.0006	0.0071	0.9315	8
Sun-Abraham	-0.1378	0.0459	0.0027	10

Note: Large p-values (> 0.05) support the parallel trends assumption. Mean pre-treatment effects near zero indicate no evidence of pre-trends. Standard errors in parentheses.

Table 16: Event Study Estimates - Selected Event Times

Dependent variable: Log Number of Schools

Period	(1) CS	(2) SA
Treatment - 2	0.0201	-0.1538
	(0.0130)	*(0.1019)*
Treatment - 1	-0.0012	-0.1747*
	(0.0098)	*(0.1010)*
Treatment (t = 0)	0.0186**	-0.4084**
	(0.0091)	*(0.2009)*
Treatment + 1	0.0304	0.0197
	(0.0196)	*(0.0123)*
Treatment + 2	0.0587*	-0.0017
	(0.0348)	*(0.0110)*
Observations	1,048	1,048
Event times shown	6	6

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. (1) Callaway-Sant'Anna (2021); (2) Sun-Abraham (2021).

Table 17: Treatment Effect Heterogeneity by Cohort

Estimator: Callaway-Sant'Anna (2021)

Cohort	ATT (with SE)	Units	Post-Treatment Periods
2007	0.0257** (0.0114)	4	5
2008	0.0027 (0.0112)	67	4
2009	-0.0030 (0.0107)	14	3

Note: ATT is the average treatment effect for units first treated in that cohort. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 18: Pre-Treatment Parallel Trends Test
Dependent variable: Log Total Students

Method	Mean Pre-Treatment Effect	SE	p-value	N periods
Callaway-Sant'Anna	-0.0015	0.0105	0.8843	8
Sun-Abraham	-0.0115	0.0285	0.6860	10

Note: Large p-values (> 0.05) support the parallel trends assumption. Mean pre-treatment effects near zero indicate no evidence of pre-trends. Standard errors in parentheses.

Table 19: Event Study Estimates - Selected Event Times

Dependent variable: Log Total Students

Period	**(1) CS**	**(2) SA**
Treatment - 2	-0.0095	-0.0233
	(0.0265)	*(0.0603)*
Treatment - 1	-0.0071	-0.0409
	(0.0120)	*(0.0577)*
Treatment (t = 0)	0.0076	-0.1162
	(0.0106)	*(0.1066)*
Treatment + 1	0.0167	0.0232
	(0.0198)	*(0.0255)*
Treatment + 2	0.0492	0.0107
	(0.0469)	*(0.0117)*
Observations	1,048	1,048
Event times shown	6	6

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. (1) Callaway-Sant'Anna (2021); (2) Sun-Abraham (2021).

Table 20: Treatment Effect Heterogeneity by Cohort
Estimator: Callaway-Sant'Anna (2021)

Cohort	ATT (with SE)	Units	Post-Treatment Periods
2007	0.0113 (0.0084)	4	5
2008	0.0100 (0.0167)	67	4
2009	-0.0096 (0.0219)	14	3

Note: ATT is the average treatment effect for units first treated in that cohort. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.