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Connected or Disturbed? Effects of Freeways on Housing Prices

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Connected or Disturbed?
Effects of Freeways on Housing Prices

Marcelo Álvez*

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Abstract

Transportation networks facilitate connectivity, which reduces trade costs and travel time. However, transportation infrastructure also generates disamenities, such as noise and air pollution. I apply a spatial difference-in-differences strategy to estimate capitalization effects of a new freeway in Phoenix, Arizona, and decompose the net effect into its accessibility and disamenity components. The new freeway reduced nearby housing prices by 12% after its announcement and by a total of 20% after it became operational. These effects diminish with distance from the freeway, and accessibility gains can mitigate the negative capitalization by more than 10 percentage points. The evidence indicates that, while new freeways improve connectivity, locally their disamenities can dominate the net capitalization effect.

Keywords: *house prices, transportation, place-based interventions, hedonic*

JEL classification: O18, R31, R40, H54

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1 Introduction

Improvements in transportation networks that increase capacity reduce travel times, which previous research has found to be beneficial at the country and metropolitan area level.[1] At the same time, transportation infrastructure produces local disamenities, such as noise, air pollution, and the risk of traffic accidents, affecting households living near roadways, and it is unclear whether accessibility improvements outweigh them.[2] Spatial heterogeneity in the net capitalization effects remains relatively unexplored, and the balance of pros and cons may differ across space.[3] Therefore, the net impact of these place-based interventions depends on the distribution of households relative to the network. Typically, identifying these two opposing forces presents a fundamental challenge, as accessibility gains and disamenities are inherently difficult to separate empirically (Kuminoff et al., 2010).

This paper uses housing-market capitalization to separately identify these two opposite effects. I first estimate the net effect of a new freeway on nearby housing prices——an asset that represents, on average, one-third of US household wealth (Sullivan et al., 2023). Then, in a novel contribution, I decompose this effect into its accessibility and disamenity components. To the best of my knowledge, this is the first study of road infrastructure to undertake such a decomposition. This analysis is policy-relevant and timely, as midcentury US highways are reaching the end of their life spans amidst declining infrastructure quality and real spending per mile that has more than tripled in recent decades (Brooks and Liscow, 2023; Conwell et al., 2023). Understanding the local effects of these large-scale place-based policies is therefore crucial for informing the forthcoming renewal of US highways, a process involving massive costs and highly variable returns to investment along the network (Allen and Arkolakis, 2022).

[1]See for example, Monte et al. (2018), Baum-Snow (2020), Jaworski et al. (2020) and Frye (2023) for the case of the US highway network, Gibbons et al. (2019) for British road network, Ahlfeldt and Feddersen (2018) for a German high-speed rail, Tsivanidis (2019) for a Bus Rapid Transit system in Bogotá, and Chen et al. (2023) for a metro system in India.

[2]See Parry et al. (2007) for a discussion on automobile externalities.

[3]Kilpatrick et al. (2007) and Cervero et al. (2009) offer previous work on roadway capitalization.

The Loop 202 South Mountain Freeway (L-202 SM) in Phoenix, Arizona, announced in April 2013 and opened in December 2019, provides a natural experiment to identify these effects. A central challenge, common to the hedonic literature, is that neither amenities nor disamenities are directly observed. I therefore infer their effects using a spatial difference-in-differences (DiD) framework. I first estimate the net effect using the ring method and then decompose this effect by leveraging the distinct spatial scales on which accessibility—shifted by ramp access—and disamenities—shifted by freeway proximity—operate.[4] This study uses a novel georeferenced dataset compiled from multiple sources, containing real estate transactions from sales deeds in Maricopa County——a large and populous metropolitan area——between January 2010 and June 2023.

The key identification challenge in a DiD strategy is selecting an appropriate control group. Given that unobserved neighborhood characteristics are shared within small geographic areas, it is desirable to compare properties within close proximity. However, properties too close are likely contaminated by spillovers (e.g., neighborhood effects). To balance this trade-off between comparability and spillovers, I implement the ring method with a buffer, also known as a donut DiD. In this strategy, I follow the literature and define treated units as properties between 2 miles from the freeway, while units between 3 and 5 miles serve as the control group. I consider a 1-mile buffer and exclude properties in that region. I expect disamenities in the 0-2 mile ring to be particularly pronounced, as the L-202 SM serves as a bypass diverting traffic—particularly freight trucks—away from Phoenix city center, potentially increasing disamenities compared to regular traffic (Li and Saphores, 2012; Muehlenbachs et al., 2021).

My estimates show that, on average, the new freeway led to a negative capitalization effect on nearby housing prices of 12% in the period leading up to its opening, an effect that deepened to a total of 20% after the freeway opened. The negative effect

[4]Diamond and McQuade (2019) discuss limitations of the ring method for recovering structural parameters but note its adequacy when focusing on reduced-form average effects on house prices, as in this case. For a comprehensive discussion of this method and its limitations, see Butts (2023).

increased over time during the pre-opening period and remained stable after the freeway opened. Upon dividing the treated region into concentric consecutive rings to allow for heterogeneous treatment effects by distance, I find the effect diminishes with distance from the freeway, consistent with an attenuation of disamenities.

To ensure the robustness of my findings, I (1) perform a repeated sale estimation, (2) use no controls, (3) omit spatial fixed-effects, (4) remove properties that could be affected by other freeways, (5) check whether treatment effects become null when moving away from the freeway before reaching the control ring, (6) perform placebo test for treatment timing and (7) treatment location, (8) apply data-driven ring cut-offs instead of those derived from prior research, and (9) check for potential confounders as supply reaction or (10) mobility changes after the Covid-19 pandemic.

Overall, this paper shows that new freeways can considerably affect nearby housing prices. However, variations in accessibility gains and exposure to disamenities can lead to substantial differences in the freeway capitalization effect. To decompose the net capitalization effect into its accessibility and disamenity components, I exploit the accessibility discontinuity provided by freeway ramps. I isolate variations in disamenities using property-level distance to the freeway and variations in accessibility gains using driving times computed through *Open Source Routing Machine* (OSRM), which depend on proximity to ramps.[5] The estimates show that differences in accessibility gains can offset the negative capitalization effect of disamenities by more than half.

Understanding these distributional impacts is fundamental for the design of transportation insfrastrcuture. In particular, I leverage my estimates to assess the capitalization effects on alternative scenarios. Adding an extra ramp could offset capitalization losses by up to $58 million through accessibility gains for the most affected properties—those next to the freeway but lacking nearby ramps. An alternative freeway

[5] I use OSRM for all travel time computations. As an open-source engine relying on *OpenStreetMap* (OSM), which is also free and open source, it ensures full replicability unlike proprietary algorithms. Building on classic shortest-path algorithms such as Dijkstra, it computes uncongested shortest paths based on average road speeds.

alignment, which reduces exposure to disamenities by shifting the freeway away from half of the treated properties, would have reduced the negative capitalization effect on those properties by 12 percentage points on median. These results highlight that key engineering decisions, such as freeway alignment and ramp location, could have led to substantial changes in capitalization.

This paper contributes mainly to two strands of literature. First, a substantial body of research examines the effects of place-based policies on property values.[6] One branch of this literature examines the capitalization effects of transportation infrastructure, though it primarily focuses on transit (Billings, 2011; Ahlfeldt et al., 2019; Gupta et al., 2022; Jerch et al., 2024). The contribution to this literature is twofold. First, I present new evidence on the capitalization of roadway infrastructure, which differs significantly from that of transit systems. Unlike transit stations, roadways do not create hubs of activity or opportunities for transport mode switching. Additionally, public transit tends to generate different and often less severe externalities than roadways. For example, Ahlfeldt et al. (2019) exclude air pollution from their analysis of the Berlin metro, as it is fully electrified. Despite these differences, the findings in this paper are in the range of impacts reported by Zhang and Yen (2020) in their meta-analysis of Bus Rapid Transit (BRT) systems. Second, to my knowledge, this is the first paper to decompose the net capitalization effect, accounting for the differential effects of accessibility gains and exposure to disamenities generated by the freeway. Previous work, as Behrens (2024), for example, exploits differential distances for identification. Analogously, I exploit differential proximity to the freeway in terms of distance and driving time to leverage the discontinuity in accessibility provided by freeway ramps. I leverage this discontinuity to isolate variations in accessibility gains, allowing for a clearer distinction between the effects of accessibility gains and disamenities.

[6] For example, Anenberg and Kung (2014); LeGower and Walsh (2017); McIntosh et al. (2018); Koster and Van Ommeren (2019); Kitchens and Wallace (2022). For reviews of the capitalization of amenities into housing prices, see Kuminoff et al. (2013); Hilber (2017); Bishop et al. (2020); Kuminoff and Mathes (2024).

Second, this paper connects capitalization estimation with the literature on roads, which typically focuses on different outcomes, like speed, distance traveled or congestion (Duranton and Turner, 2011; Couture et al., 2018; Kreindler, 2024). Relevant to understanding the multidimensionality of freeway disamenities, several studies provide evidence of each of these traffic externalities individually. For example, Viard and Fu (2015); Gibson and Carnovale (2015); Chen et al. (2016); Sleiman (2023) on air pollution, Wilhelmsson (2000); Von Graevenitz (2018); Wang et al. (2023) on noise pollution, Currie and Walker (2011); Anderson (2020) on health, and Nehiba and Tyndall (2023) on pedestrian fatalities. This paper estimates the net capitalization effect, accounting for the full set of disamenities and the countervailing accessibility gains.

Closer to this paper, Brinkman and Lin (2022) study the long-run effects of freeways on population changes at the census tract level.[7] They highlight the trade-off between accessibility and disamenities and propose a functional form for disamenity fade-out, which I build upon.[8] By using granular, property-level transaction data, I estimate the direct capitalization effect on housing prices. This allows me to provide insight into the importance of local disamenities in the short run, including the crucial anticipation period before the freeway opens. Most critically, by using property-level data, I can exploit the sharp, differential variation in a property's distance and driving time to the freeway for identification. This requires parcel-level data, as the critical variation is lost at the tract level.

The rest of the paper proceeds as follows. Section 2 describes the institutional setting and data. Section 3 estimates and analyzes the net capitalization effect of L-202 SM. Section 4 decomposes this net effect, distinguishing between accessibility gains and exposure to disamenities generated by the freeway. Section 5 addresses threats to identification. Section 6 discusses alternative scenarios. Finally, Section 7 concludes.

[7] Related, Duranton and Turner (2012) study the US highway network long-run effect on population growth, Valenzuela-Casasempere (2024) on individuals' mortality, and Mahajan (2024) and Weiwu (2024) on racial segregation.

[8] They argue that the local impact of freeways is more pronounced in urban settings, as in this paper, and less negative in suburban areas.

2 Institutional Setting and Data

2.1 Loop 202

The Loop 202 surrounds the Phoenix metropolitan area from the East and South. It complements the existing Loop 101 surrounding Phoenix by the North and Loop 303, which extends the connectivity to the West. This freeway network facilitates traveling in a flat-built car-oriented city that extends over 9,000 square miles and is populated by more than 4 million people.[9] Figure 1 shows these beltways.

The Loop 202 was built in three separate branches: San Tan opened in 2006, Red Mountain opened in 2008, and South Mountain opened in 2019. All of them were part of a comprehensive regional transportation plan initially approved by Maricopa County voters in 1985. However, the latter, officially named Congressman Ed Pastor Freeway, was planned on native land and did not have neighbors' approval. During the thirty-plus years following its initial proposal, there was much uncertainty regarding whether it would be built. Moreover, in the case that it were built, there was uncertainty about its location.

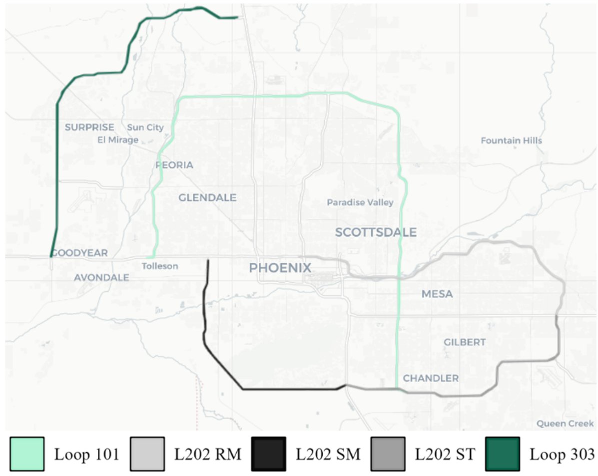
In April 2013, the Arizona Department of Transportation (ADOT) and the Federal Highway Administration (FHWA) released a Draft Environmental Impact Statement (DEIS). This document made clear that they would finally build the freeway and reduced the uncertainty about its location (ADOT, 2024b).[10]

The DEIS projected that by reducing congestion, travel times within the region would improve, yielding an estimated annual savings of $200 million in travel time. However, this metropolitan-level benefit was expected to come with local costs. The DEIS anticipated that the proposed freeway would increase traffic volumes and, conse-

[9]Maricopa County was the fourth most populated county and Phoenix the fifth most populated city in 2023 according to the United States Census Bureau (Bureau, 2024).

[10]ADOT originally planned to place the freeway in the native land of the Gila River Indian Community (GRIC), but strong opposition from GRIC residents blocked this option. After unsuccessful negotiations, ADOT decided to place the freeway outside native land. Once the decision was made to avoid GRIC land, the freeway's alignment became exogenous due to geographical constraints, as there was no alternative location between South Mountain and the GRIC border.

Figure 1: Phoenix Metropolitan Area



Notes: The map depicts the Phoenix metropolitan area and its three beltways: Loop 101 (light green), Loop 202 (shades of gray), and Loop 303 (dark green). The Loop 202 South Mountain Freeway is shown in black. The other segments that form the Loop 202 are San Tan in dark gray and Red Mountain in light gray.

quently, local emissions of carbon monoxide, particulate matter, and mobile-source air toxics in the proximity of the freeway. It also highlighted other adverse effects associated with the project, including visual and noise intrusions into existing neighborhoods and the loss of water resources.[11] Therefore, given this discussion, expecting an anticipatory effect for the future freeway is prudent.

Two years after the DEIS, the agencies released the final version of the Environmental Impact Statement, reinforcing the information provided by the former. The following year, the construction of the L-202 SM started in September 2016 in the location anticipated by the DEIS.

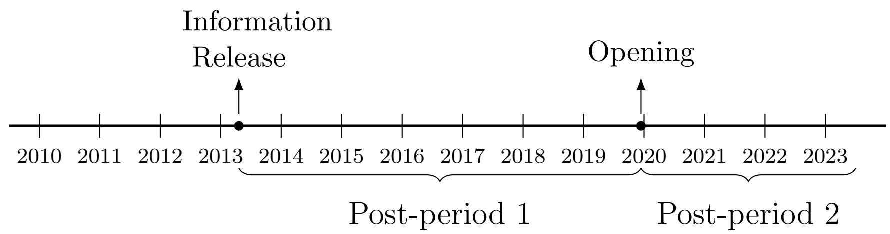
Finally, another milestone was on December 21, 2019, when L-202 SM opened to traffic. Since then, information about new travel times, noise pollution, and other

[11] Interestingly, the DEIS includes areas of concern. Among them, it points out the public comments suggesting the proposed freeway would function primarily as a bypass for trucks. It explicitly recognized that commercial trucks would use the proposed freeway. However, the DEIS tried to mitigate the concerns and stated that it was not expected that the entire volume of truck traffic using I-10 would divert from I-10 to the proposed freeway. This mitigation action by ADOT reflects that agents would expect heavy traffic on this future freeway; the traffic negative externalities would differ if the vehicles were mainly cars or trucks (Li and Saphores, 2012; Muehlenbachs et al., 2021).

negative externalities has been publicly available.

The 2 milestones mentioned before, information released by the DEIS and opening, define the treatment timing and the post-period division in the empirical strategy. Figure 2 illustrates the timeline.

Figure 2: Timeline of the Loop 202 South Mountain Freeway



2.2 Data

The primary data sources are records from housing transactions and deeds collected by the Maricopa County Recorder's Office, which I merge with the Maricopa Assessor's Office's property characteristics and geolocation data. Appendix B provides descriptive statistics on these variables.

The final dataset involves three cuts. First, transactions involving properties located outside the analyzed region (5 miles from the freeway) are excluded, as detailed in Section 3.1. Second, only arm's-length transactions are included. The selected transactions ranging from January 2010 to June 2023 involve single-family properties, one-parcel transactions, transactions where the buyer and seller are different entities, and transactions classified with an assessor's code that does not suggest a non-market price.[12][13] Third, I drop transactions corresponding to properties in the first and ninety-ninth percentiles of the distribution of livable area or lot size. As shown in Table 1, my final sample contains 44,422 transactions.

[12] I start the sample in January 2010 to avoid the volatility produced during the Subprime Mortgage Crisis.

[13] The assessor's office assigns an assessor's code, which includes some red flags pointing to transactions that may not reflect market prices.

Additional sources facilitate complementary georeferenced data. I get Census spatial delimitations using the *tigris* R package and rely on OSM to obtain additional georeferenced data on roadways to compute distances using the *sf* R package.

Finally, I obtain uncongested travel times using OSRM, a routing engine that computes the fastest route based on the road network provided by OSM. For each property, I compute the fastest route from and to the freeway in both the West and East directions. This information is relevant for the identification strategy in Section 4.[14]

Table 1: Descriptive Statistics

	Before Info. Jan2011-Mar2013 (1)	After Info. Apr2013-Dec2019 (2)	After Opening Jan2020 onward (3)
Num. of Sales			
Control	3,212	9,140	4,546
Treated	5,399	15,102	7,023
Ring 1	571	1,751	915
Ring 2	2,315	6,624	3,015
Ring 3	2,513	6,727	3,093
Mean Price			
Control	126,855	214,415	374,863
Treated	194,375	280,974	456,875
Ring 1	213,096	302,823	473,969
Ring 2	200,424	285,629	463,746
Ring 3	184,549	270,702	445,120

Notes: The table presents the number of sales and the mean transaction prices during the three subperiods of interest for the control group, treated group, and each of the rings defined in Section 3.1. Column (1) reports transactions from the pre-period, which occurred before the Arizona Department of Transportation released the Draft Environmental Impact Statement in April 2013, a point after which the likelihood of the freeway being built increased significantly. Column (2) details transactions from post-period 1, spanning from April 2013 to December 2019, following the information release but before the freeway's opening. Column (3) shows transactions from post-period 2, which begins after the Loop 202 South Mountain Freeway opened in December 2019. The rings are subsets of the treated group, categorized by proximity to the freeway: ring 1 includes properties within 0.25 miles of the freeway, ring 2 covers properties between 0.25 and 1 mile, and ring 3 includes properties between 1 and 2 miles.

[14]For recent contributions employing navigation and route-finding software tools in urban economics see for example Duranton (2015); Couture et al. (2018); Balboni et al. (2020); Baum-Snow et al. (2020); Akbar et al. (2023); Conwell et al. (2023); Barwick et al. (2024); Kreindler (2024).

3 Freeway Net Capitalization

3.1 Difference in Differences

Empirical Strategy

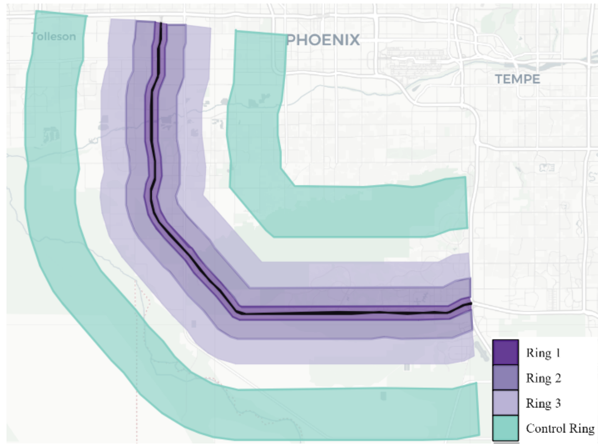
As shown in Figure 2, I distinguish two post-periods. The first begins in April 2013 with the release of the DEIS and ends in December 2019, when the L-202 SM opened and Post-period 2 begins. This design, which I extend later in a more granular event study, points to a clear distinction between the anticipatory effects and the effects once the freeway opens, when households enjoy accessibility gains and suffer traffic externalities. The effects observed during Post-Period 1 may reflect other factors beyond pure anticipation. For example, the construction of the freeway itself could generate temporary impacts. Although they are more likely to capitalize on rents rather than prices due to their transitory nature. Nonetheless, distinguishing between these two subperiods clarifies which portion of the price adjustment occurs in anticipation of the freeway and which reflects its realized impact.

Treatment is geographically defined by the location of the new freeway. I employ the ring method to assign treated and control status. The identification strategy compares properties in an inner treated ring, closest to the freeway, with those in an outer control ring, located slightly farther away.[15] Figure 3 illustrates this approach. The comparison is motivated by the physical proximity of the units, assuming that they are exposed to common shocks over time.

Under the assumption that treatment effects diminish over space until they dissipate, the choice of the control group implies an econometric trade-off. On the one hand, one wants to minimize the treatment effect on the control group (far from the freeway) and, on the other hand, maximize similarity in terms of common drivers of real estate

[15] Previous studies applied this method to measure the effect of spatially-targeted treatments. For instance, Currie et al. (2015) for pollutant plants,Aliprantis and Hartley (2015) for public housing demolitions, and Shoag and Veuger (2018) for big stores.

Figure 3: Treated and Control Regions



Notes: The map illustrates the empirical design, displaying the theoretical definition of regions. Each unit within a region is assigned to its corresponding group. The treated rings are shaded in violet, the control region in green, and the buffer region, located in between, is uncolored. The treated rings are subsets of the overall treated area, classified by their proximity to the freeway. Properties within 0.25 miles of the freeway are in Ring 1, those between 0.25 and 1 mile in Ring 2, and those between 1 and 2 miles in Ring 3. The buffer region spans 2 to 3 miles from the freeway, while the control region extends from 3 to 5 miles. The Loop 202 South Mountain Freeway is depicted in black.

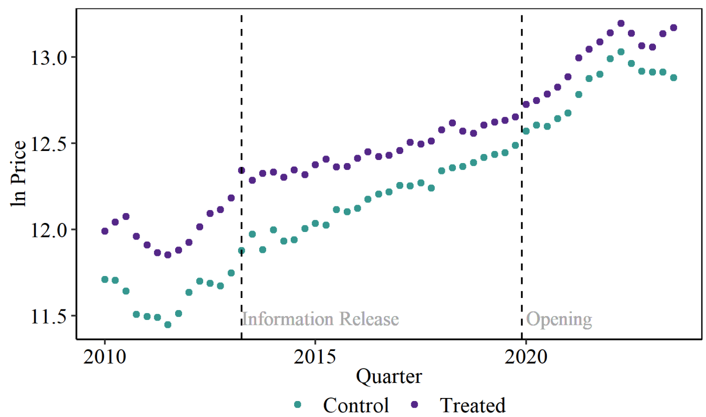
valuations (close to the treated group, hence to the freeway). To support the former, I leave a buffer between treated and control units, defining an intermediate ring of units excluded from the sample. This buffer minimizes any potential direct or spillover effects on the control group.[16]

Intervals reported in the literature for the spatial extent of different sources of disamenities drive my choice of ring width. The first specification, presented in Equation 1 and extended later, defines the treated ring width as 2 miles. This distance is enough to dissipate negative externalities (argued below) and accessibility improvement. It takes at most 7 minutes to reach L-202 SM by car for 97% of the properties within 2 miles of the freeway.

The width of the buffer is 1 mile. Thus, it extends from 2 to 3 miles from the freeway. Brinkman and Lin (2022) state that freeway amenities are attenuated by 95% at 2.4 miles, and local dynamic effects and barrier effects extend up to 3 miles.

[16] Excluding properties in the buffer region from the analysis contributes to achieving a null contamination term in the framework of Alves et al. (2023).

Figure 4: Raw Data



Notes: Each dot represents the quarterly mean log-price of transactions for both the treated and control groups. Vertical lines indicate key events: the release of information and the freeway's opening. The treatment began in April 2013 when the Arizona Department of Transportation released the Draft Environmental Impact Statement, significantly increasing the likelihood of the freeway's construction. Post-period 1 concludes in December 2019, when the Loop 202 South Mountain Freeway officially opened to traffic. Post-period 2 extends from that point onward.

The control ring extends from 3 to 5 miles from the freeway. For 99% of the properties in this region, it takes at least 7 minutes to reach L-202 SM by car, and it is not in their time-minimizing route to the major employment centers in the metropolitan area computed by Ahlfeldt et al. (2025), as detailed in Table C1 in the Appendix.

Figure 4 shows raw price data for the treated and control groups. Each point indicates the quarterly mean of the log-price for the corresponding ring. Visual inspection illustrates the quasi-experimental design. The difference between both series remained stable until the start date of the treatment, when information about the future freeway was released. This suggested parallel trajectory before the treatment is confirmed when running a pre-test, I cannot reject the absence of pre-trends. Once ADOT published the DEIS, the difference between them decreased gradually during post-period 1, until the freeway opening date, and the difference seemed to remain stable afterward, during post-period 2. The movement of prices in Figure 4 seems to reflect the gradual incorporation of new information until the freeway opened.

My baseline specification allows for some degree of heterogeneous effects over time and averages spatial effects within the treated region. I estimate two post-period coefficients to separate anticipatory and post-opening effects. Equation 1 formalizes my first specification:

$$\begin{aligned} \ln \mathit{price}_{it} = \beta_0 + \beta_{treated}\mathbb{1}(\mathit{treated}) + \gamma_1\mathbb{1}(\mathit{post\text{-}period}\ 1)\mathbb{1}(\mathit{treated}) + \\ + \gamma_2\mathbb{1}(\mathit{post\text{-}period}\ 2)\mathbb{1}(\mathit{treated}) + \mathbf{X}\boldsymbol{\beta} + \lambda_t + \alpha_{location(i)} + \varepsilon_{it} \end{aligned} \tag{1}$$

Where $\mathbb{1}(\mathit{treated})$ is an indicator variable for property i belonging to the treated ring, $\mathbb{1}(\mathit{post\text{-}period}\ 1)$ is an indicator variable for the observation in time t corresponding to the first post-period (Apr2013 $\leq t \leq$ Dec2019) and $\mathbb{1}(\mathit{post\text{-}period}\ 2)$ is an indicator variable for the observation corresponding to the second post-period ($t \geq$ Jan2020). The vector $\mathbf{X}$ of control variables includes the livable area of the property (in sq. ft.), an indicator for the property having a pool, the lot size (in sq. ft.), the number of bathroom fixtures, and the age of the property. λ_t corresponds to the quarter-year fixed effects, and $\alpha_{location(i)}$ represents fixed effects at the location of i, which is the census block group in the baseline specification, and ε_{it} is the error term. The coefficients of interest are γ_j, which identify the average treatment effect on the treated properties during post-period $j \in \{1, 2\}$.

Channels of Capitalization

This paper quantifies the net capitalization of freeways on nearby housing prices, beyond any metropolitan-wide capitalization effects. In doing so, it makes a novel contribution by decomposing this net effect into two opposing components: accessibility gains and local disamenities, which is presented in Section 4. While a finer dissection of these components—particularly the latter, which encompasses a bundle of individual disamenities—is left for future work, it is useful to summarize the potential channels through which freeway capitalization is expected to operate. This framework provides a clean empirical separation of the two primary forces.

First, a central benefit of new transportation infrastructure is improving accessibility. The new freeway is expected to reduce travel times to locations that were previously connected only through longer routes involving minor roads. Shorter driving times to destinations of interest, like major employment or consumption centers, should have a positive effect on home values.

Second, these gains are expected to be partially or fully offset by the capitalization of traffic-related disamenities. Proximity to a freeway can negatively affect health and well-being through increased exposure to air pollution, noise, and a higher risk of traffic accidents. Moreover, changes in traffic patterns may also induce congestion on parts of the roadway network, such as minor roads leading to ramps, while visual pollution (e.g., lighting) can further compound these local negative effects.

The reduced-form DiD framework estimates the net capitalization effect, which reflects the equilibrium outcome of these two opposing forces. It is important to be precise about what this estimate captures. The introduction of a freeway may also induce further general equilibrium adjustments, such as changes in the provision of local amenities (e.g., retail) or the sorting of households based on their preferences for accessibility versus environmental quality. Because these adjustments are themselves endogenous responses to the freeway, the DiD estimate captures the total, combined impact of the direct accessibility/disamenity channels and these induced local changes. While my empirical strategy does not separately identify these latter GE channels, they are a direct consequence of the new freeway and are therefore correctly included as part of the total capitalized effect on local property values.

Results

Table 2 shows OLS estimates of Equation 1. Column (1) shows the most parsimonious model, including only time fixed-effects. Column (2) adds housing characteristics, and

Column (3) adds spatial fixed-effects. Column (4) restricts the sample to properties sold in at least two of the three subperiods of interest (pre, post 1, and post 2) and includes a house FE instead of the block group FE.

The estimates are stable across specifications. My preferred specifications are the last two columns because they account for unobservable characteristics of the location (3) or the property (4). In the remainder of the paper, I use the full sample to preserve statistical power, as the repeated-sales approach reduces the sample size by more than half.

Table 2 shows there is an anticipatory effect. Nearby property prices reacted to the announcement of a future freeway years before the freeway was in place. The anticipatory effect of the freeway on nearby property prices was between -12.07% (i.e., $e^{-0.1286}-1$) and -10.56% depending on whether I control for location or unit fixed effects. And the accumulated effect reached -19.75% and -17.40% after the freeway opened.

Table 2 reports standard errors clustered at the block group level. I use this clustering level in all specifications following Abadie et al. (2023), as the treatment mainly varies at the block group level.[17]

Discussion

The estimates in Table 2 show a large effect on nearby property prices. These results are robust to several robustness checks in Section 5.[18] In this section, I focus on understanding the magnitude of these effects and comparing my estimates with those in prior literature.

There are two reasons to expect a large impact of disamenities in this particular

[17]My preferred specification already includes quarter-year fixed effects (λ_t), which absorb aggregate temporal shocks that affect all properties simultaneously. Once these common time trends are captured by fixed effects, the remaining correlation structure is primarily spatial rather than temporal. This approach aligns with the design-based framework proposed by Abadie et al. (2023), which recommends clustering at the level of treatment assignment. There is minimal variation in treatment assignment within block groups. Only two of the 138 block groups in my sample have treated and untreated units.

[18]The results are also robust to alternative specifications. In Appendix L, an alternative partition that disregards the theoretical intervals and excludes the buffer ring produces similar results.

Table 2: Difference in Differences

	Dependent variable: ln Price			
	(1)	(2)	(3)	(4)
Post-period 1	-0.1143^{***}	-0.0991^{***}	-0.1286^{***}	-0.1115^{***}
	(0.0401)	(0.0374)	(0.0338)	(0.0380)
Post-period 2	-0.2065^{***}	-0.1894^{***}	-0.2200^{***}	-0.1911^{***}
	(0.0561)	(0.0502)	(0.0471)	(0.0497)
Housing Controls	No	Yes	Yes	Yes
Time FE	Quarter-Year	Quarter-Year	Quarter-Year	Quarter-Year
Spatial FE	No	No	Block-Group	House FE
Observations	44,422	44,422	44,422	18,096
R^2	0.4807	0.7640	0.9005	0.9511

Notes: The table presents OLS estimates from Equation 1. Column (1) includes only time fixed effects. Column (2) incorporates housing characteristics as controls, while Column (3) adds spatial fixed effects. Column (4) introduces unit fixed effects, restricting the sample to properties sold in at least two of the three subperiods of interest (pre-period, post-period 1, and post-period 2). Housing controls include livable area, presence of a pool, lot size, number of bathroom fixtures, and house age. Standard errors are clustered at the block group level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

setting: the initial level of natural amenities and the characteristics of L-202 SM traffic. This freeway was built near pre-existing high-value properties, part of whose value likely comes from their separation from the urban area and proximity to open space (Anderson and West, 2006; Klaiber and Phaneuf, 2010). In particular, properties in the southern region benefit from the landscape and natural amenities that South Mountain provides, as well as the green areas on native land. Moreover, South Mountain acts as a barrier to pollution generated in urban areas. L-202 SM brings traffic disamenities into these neighborhoods, substantially altering their natural surroundings. For example, L-202 SM truck traffic generates larger disamenities compared to a freeway whose traffic is mainly cars (Li and Saphores, 2012; Muehlenbachs et al., 2021). Therefore, one might expect large effects of L-202 SM on these self-selected naturally surrounded properties compared to other contexts.

The estimates are in line with the few similar examples that exist in the literature. Bagagli (2023) estimates Chicago's expressways had an effect of -16.25% on house value and -0.2 log points on land value, which are similar to Table 2. Connolly et al. (2019) find that living near a major road is associated with a 6% decrease in housing price. A lower impact is consistent with freeways generating more disamenities than major roads.

There are also estimates for particular externalities that align with mine, e.g. traffic noise. Wilhelmsson (2000) finds a discount of 0.6% per decibel that reaches a total discount of 30% for single-family houses near a road where noise is loud in Sweden. Wang et al. (2023) find that traffic noise decreases housing rents by 12.7% in Singapore, and Diao et al. (2016) find in Malaysia that removing train noise increases housing prices by 13.7%.

Beyond roadways, my estimates fall within the range of those for the capitalization of BRT collected by Zhang and Yen (2020) in their meta-analysis, between -18.7% and 26.0%, and are closer to the more negative end of Acton et al. (2022) estimates, ranging between -11.4% and 4.2% for 11 BRT in the U.S.

3.2 Temporal Heterogeneity

In an event study design, I estimate quarterly effects. Equation 2 formalizes this specification. It differs from Equation 1 by including a separate $\gamma_{t'}$ for each quarter, rather than aggregating them into two subperiods:

$$\begin{aligned} \ln price_{it} = \beta_0 + \beta_{treated}\mathbb{1}(treated) + \\ + \sum_{t' \neq -1} \gamma_{t'}\mathbb{1}(treated)\mathbb{1}(t = t') + \mathbf{X}\boldsymbol{\beta} + \lambda_t + \alpha_{location(i)} + \varepsilon_{it} \end{aligned} \tag{2}$$

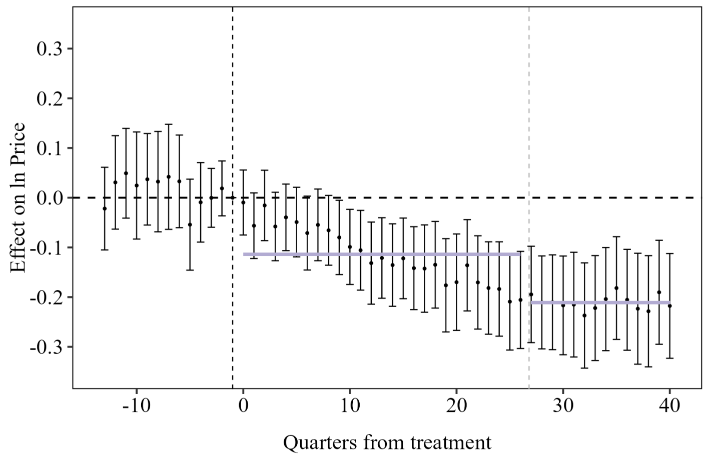
Where t denotes quarters since the information release, with quarters before the information release taking negative values. Each of γ_t coefficients identifies the average treatment effect on the treated after t periods from the information release. $t = -1$ is the reference category excluded from the regression. Thus, the treatment effects are measured relative to the quarter before the information release, when I expect the treatment effect to be null. The remaining variables are as described in Equation 1.

Figure 5 plots the coefficient estimates. The vertical dotted lines show the milestones delimiting post-period 1 and post-period 2. Starting from left to right, the estimated coefficients corresponding to quarters before the information release ($t < 0$) are centered around zero, suggesting the absence of pre-trends.[19] The treatment effects decreased during the pre-opening period and stabilized around the opening. This result reinforces visual inspection of the raw data in Figure 4. The horizontal lines show the average of the quarterly average treatment effect on the treated (ATT) during the two post-periods. The average ATT during the pre-opening period masks a decreasing ATT during the 27 quarters following the information release. Contrarily, the average effect during the post-opening period is similar to the treatment effect for each quarter.[20]

[19] I cannot reject the "pre-test" of $\gamma_t = 0 \quad \forall \quad t < 0$ at the usual significance levels. This result supports the lack of preexisting trends in price changes before treatment.

[20] Note that the difference between the average of the quarter effects in the pre and post-opening and the estimates in Table 2 is tiny. Goodman-Bacon (2021) states that large differences would suggest problems associated with OLS weights. This is not the case in this paper since all the treated units

Figure 5: Event Study



Notes: The dots represent OLS estimates for γ_t in Equation 2, capturing the average treatment effect on the treated (ATT) for the log of prices accumulated after t periods from the information release. The quarters on the x-axis are defined relative to the treatment start date (the information release in April 2013), with $t = -1$ serving as the reference category. The vertical dashed lines mark the boundaries between the two post-periods. The horizontal violet lines indicate the average ATT during each post-period. The bars represent 95% confidence intervals for each coefficient, with standard errors clustered at the block group level.

The gradual increase in treatment effects observed during Post-Period 1 suggests that the capitalization process unfolded over time rather than occurring immediately after the DEIS release. At least three mechanisms could explain this pattern. The first is information frictions: it may take time for market participants to learn about the DEIS release and incorporate this information into property valuations. A second mechanism is household sorting. New residents may hold different valuations of accessibility and traffic disamenities, gradually affecting capitalization as they relocate. As an initial exploration of this mechanism, I examine changes in household composition at the block-group level. As shown in Table D1 in the Appendix, the composition of households in the treated region appears to have shifted toward lower income and educational attainment, suggesting that sorting may indeed be occurring. However, because the parcel data do not include individual resident characteristics, a more detailed analysis of sorting is left for future research, conditional on data availability.

are treated simultaneously.

A complementary interpretation arises from asset pricing theory. If property prices reflect the present discounted value of future rental flows, and rents adjust in response to proximity to the freeway, then the convergence of treatment effects during Post-Period 1 toward the levels observed in Post-Period 2 may represent the adjustment of property values toward the fully capitalized rent flow as the opening date approaches. Appendix F provides a back-of-the-envelope calculation consistent with this interpretation. The implied spread of 5.7 percentage points relative to the average 30-year fixed mortgage rate in the United States during the same period supports the plausibility of this asset-pricing channel, though it likely operates alongside other channels such as information frictions and sorting.[21]

3.3 Spatial Heterogeneity

This section explores the heterogeneity of treatment effects over space. I divide the treated ring into three concentric rings to estimate separate treatment effects for each. The width of the rings follows distance intervals reported in the literature for the spatial extent of different sources of disamenities, providing a basis for interpretation.[22] Ring 1 contains properties within 0.25 miles of the freeway, which can be associated with the scope of noise pollution (Von Graevenitz, 2018; Ahlfeldt et al., 2019) and effects on pedestrian fatalities (Nehiba and Tyndall, 2023). Ring 2 extends from 0.25 to 1 mile from the freeway, which can be interpreted by thinking about the extension of air pollution (Currie and Walker, 2011; Currie et al., 2015; Viard and Fu, 2015; Han et al., 2020). The remaining properties in the treated ring belong to Ring 3.[23] Figure 3

[21]The construction of the freeway itself could have an effect during Post-Period 1. Although, as mentioned above, its capitalization on home prices is expected to be limited due to their transitory nature.

[22]These intervals should not be interpreted as hard thresholds for the spatial reach of each disamenity. They are drawn from diverse contexts and serve only as reference points to help interpret the results.

[23]Note that these references are subject to the caveat that the geographical characteristics of Beijing, Berlin, Denmark, and US cities from Currie and Walker (2011) and Currie et al. (2015) (Florida, Michigan, New Jersey, Pennsylvania, and Texas) differ from the desert valley of Phoenix. Notably, the European cities have more trees, which can reduce traffic pollution, as noted by Ren et al. (2023). Even tree characteristics matter (Zhao et al., 2021). Moreover, pollution can also travel different distances

illustrates this specification, formalized in Equation 3.[24] Relative to Equation 1, it allows for a distinct coefficient, γ_{jr}, for each combination of subperiod j and ring r, rather than grouping all rings together.

$$
\begin{aligned}
\ln price_{it} = \beta_r \mathbb{1}(ring_i = r) + \sum_r \gamma_{1r} \mathbb{1}(\text{post-period 1}) \mathbb{1}(ring_i = r) + \\
+ \sum_r \gamma_{2r} \mathbb{1}(\text{post-period 2}) \mathbb{1}(ring_i = r) + \mathbf{X}\boldsymbol{\beta} + \lambda_t + \alpha_{location(i)} + \varepsilon_{it} \qquad (3)
\end{aligned}
$$

Where $\mathbb{1}(ring_i = r)$ are indicator variables for unit i belonging to ring r, for $r \in 1, 2, 3$. γ_{jr} captures the average treatment effect in post-period $j \in \{1, 2\}$ for ring $r \in \{1, 2, 3\}$.

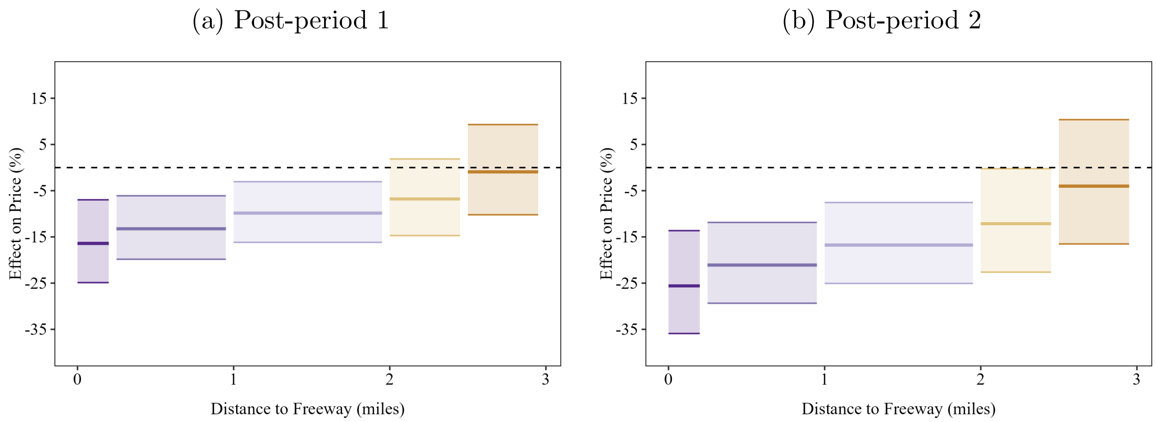
Figure 6 reports the estimates for this specification in violet; Panel (a) reports the estimates for ATT during post-period 1 and Panel (b) during post-period 2. It also adds two additional rings placed within the buffer. Ring 4 is defined as the inner half of the buffer, between 2 and 2.5 miles from the freeway. Ring 5 is defined as the outer half, between 2.5 and 3 miles, as shown in Figure A2.

As before, the negative estimates for post-period 1 identify an anticipatory effect. House prices responded before the freeway was in place. In both post-periods, the treatment effect falls towards zero when moving away from the freeway (to the right in Figure 6). The average treatment effect for units treated in ring 1, the closest to the freeway, is -16.41% during the pre-opening period and increases to -25.6% during the post-opening period. These properties experienced the largest treatment effects. Intuitively, they are the most exposed to disamenities. The average treatment effect in ring 2 is -13.24% during the pre-opening period and -21.09% post-opening, while it is -9.85% and -16.77% for units in ring 3. Figure E1 in the Appendix compares anticipatory

and directions related to wind, as Heblich et al. (2021) point out. Nonetheless, these intervals allow me to estimate heterogeneous effects by distance with an intuitive interpretation. As mentioned above, identifying the separate contribution of each disamenity exceeds the scope of this paper.

[24] Figure A1 in the Appendix maps the properties sold during the analyzed period in each ring.

Figure 6: Heterogeneous Treatment Effects by Distance from the Freeway



Notes: The figure displays the average treatment effect on the treated (ATT) on prices in each post-period across varying distances from the freeway. The effect is calculated as $(e^{\gamma} - 1) * 100$ where γ is the OLS estimates for γ_{1r} and γ_{2r} from Equation 3 in panels (a) and (b), respectively. Note that γ_{2r} reflects the total effect since the start of the treatment. The inner lines represent the point estimates, while the outer lines denote the 95% confidence intervals based on standard errors clustered at the block group level. Figure A2 shows these regions.

and total effects by overlapping them on top of each other. The anticipated effect is approximately 60% of the total effect, indicating the relevance of the information release.

Both figures exhibit the same pattern; the treatment effects attenuate until converging to the null effect as one moves away from the freeway. Although estimates for rings 4 and 5 are not statistically distinguishable from zero, they could suggest spillover effects over ring 4 due to its proximity to the treated units. As one moves away from the freeway, these effects dissipate once in ring 5. These estimates empirically reinforce the ring width definition from Section 3.1. The buffer isolates any possible spillover effects captured by Ring 4. And when moving away from the freeway, the treatment effects become null before reaching the control ring.

Figure K1 in the Appendix illustrates a finer spatial heterogeneity reporting treatment effects in 0.25-mile intervals. It reinforces the gradual decay of the effect with distance, while showing a smooth transition between rings, indicating that the chosen intervals do not represent hard thresholds but rather serve as a useful reference for interpreting the results as discussed above.

As a sensitivity analysis on the choice of rings, Figure L1 in the appendix plots the estimates of the effect of L-202 SM on nearby property prices using an alternative definition of rings. Each ring corresponds to a quintile of the distribution of distance from L-202 SM in the analyzed region, within 5 miles from L-202 SM. Quintiles is the optimal partition according to the procedure in Cattaneo et al. (2024) for this dataset.[25] The estimates show the change in price relative to the last quintile; they exhibit a similar pattern as in Figure 6, the effect attenuates with distance, and the effects become null within the buffer after 2.5 miles.

4 Decomposing Positive and Negative Amenities

Empirical Strategy

To disentangle the effects of accessibility gains from those of disamenities, it is necessary to isolate variation in one dimension while holding the other constant and accounting for resulting differences in treatment effects. I do so by exploiting variation in exposure to disamenities, captured by distance from the freeway, and variation in accessibility gains, measured by off-freeway driving time to the nearest ramp. This identification strategy leverages the discontinuities in accessibility gains introduced by ramp locations and requires the following two assumptions.

First, I assume that traffic disamenities extend perpendicular to the freeway. Accordingly, differences in distance from the freeway capture variation in exposure to disamenities, following the reasoning outlined in Section 3.3.[26]

Second, I assume that the accessibility gains provided by the freeway consist of two components: a common component shared by all households and a variable component

[25] This strategy is suggested by Butts (2023) for ring method applications.

[26] As previously noted, geographic characteristics can affect exposure to specific disamenities such as noise and air pollution. Therefore, exposure to individual disamenities may vary even at the same distance. The objective of this paper, however, is not to isolate the effect of each disamenity separately but to identify their combined effect. The key assumption is that overall exposure to disamenities increases with proximity to the freeway.

that depends on each property's connectivity to the freeway. The latter can be proxied by off-freeway driving time. Because households can access the freeway only through ramps, accessibility gains are expected to be larger for properties requiring shorter trips to reach a ramp than for those requiring longer trips. Accordingly, off-freeway driving time captures the heterogeneous component of accessibility gains. To ensure that this measure reflects the most relevant access conditions for each household, I compute the average off-freeway driving time across the four possible directions.[27] Notably, there may be differences in the initial level of accessibility across space that matter for capitalization. I include spatial fixed effects to control for those differences.

Using off-freeway driving time is, however, a second-best approach. Ideally, I would use changes in a market-access measure before and after the freeway's opening to capture accessibility gains. Unfortunately, pre-treatment driving times are unavailable, preventing the computation of such changes.[28]

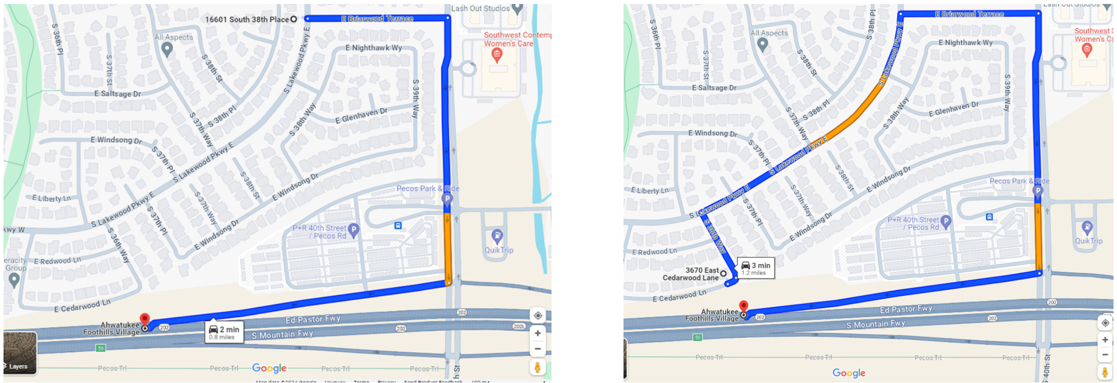
Figure 7 shows how a property located at a short distance from the freeway (exposed to a high level of disamenities) can have lower accessibility gains provided by the freeway than another that is at a longer distance. These patterns arise from the discontinuities generated by ramp locations. Figure 8 illustrates the variability in accessibility gains within the analyzed region. Properties near ramps exhibit larger accessibility gains (lighter colors) than those farther from ramps but at a similar distance from the freeway,

[27] The four directions are: (i) from the freeway to the property heading South (East), (ii) from the freeway to the property heading North (West), (iii) from the property to the freeway heading South (East), and (iv) from the property to the freeway heading North (West). Each trip involves a distinct entry or exit, and thus a different driving time. The relevant subset of trips may vary across households depending on their destination of interest. Because these destinations are unobserved, I take the average across all four directions to capture relative differences in accessibility gains.

[28] As an exploratory exercise, I analyze the relationship between driving time to the freeway and driving time to major employment centers defined by Ahlfeldt et al. (2025), as a measure of labor market access. Table C2 in the Appendix shows a positive relationship between driving time to L-202 SM and driving time to prime locations. After controlling for spatial fixed effects (which capture the initial level of accessibility at the block-group level) and distance to L-202 SM, driving time to L-202 SM explains 38% of the variation in average driving time to prime locations among treated properties. While comparing ex-post driving times cannot fully capture variation in labor market access, this analysis suggests that driving time to the freeway captures a sizable share of the variation in access to prime locations.

Figure 7: Accessibility and Disamenities

(a) lower disamenities higher accessibility (b) higher disamenities lower accessibility



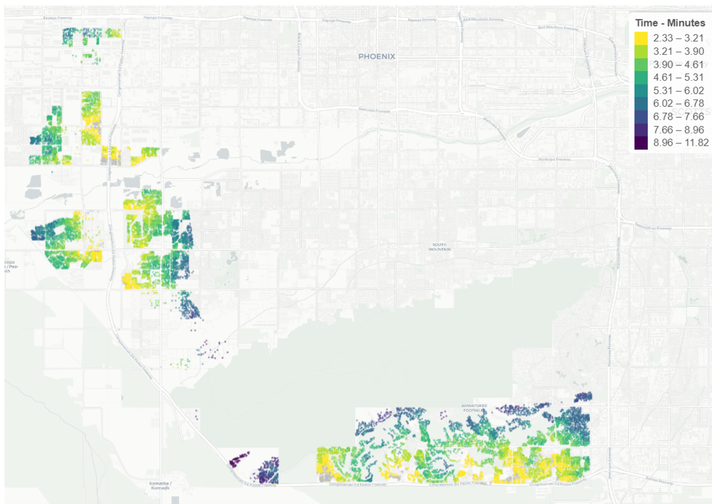
Notes: The figure, taken from *GoogleMaps*, illustrates how a property located closer to the freeway, and thus exposed to higher levels of negative externalities, may experience lower accessibility gains compared to a property situated farther away. In panel (a), the property is closer in driving time to the freeway compared to the property in panel (b), even though it is physically farther from the freeway. These patterns emerge due to the discontinuities introduced by freeway ramps, which influence the balance between accessibility gains and exposure to disamenities.

and hence subject to comparable levels of disamenities. Exploiting this variation, I estimate heterogeneous effects of L-202 SM on housing prices by accessibility gains and exposure to disamenities through Equation 4. Relative to Equation 1, this specification allows for a distinct coefficient, γ_{jrm}, for each combination of subperiod j, disamenity bin r and accessibility bin m, rather than imposing a common effect across all bins. Disamenity bins are defined using the same rings as in Section 3.3, and accessibility bins correspond to terciles of off-freeway driving time among treated properties.

$$
\begin{aligned}
\ln price_{it} = \beta_0 + \sum_r \beta_r \mathbb{1}(\text{ring} = r) + \sum_m \beta_m \mathbb{1}(\text{time} = m) + \\
+ \sum_{r,m} \gamma_{1rm} \mathbb{1}(\text{post-period } 1, \text{ring} = r, \text{time} = m) + \\
+ \sum_{r,m} \gamma_{2rm} \mathbb{1}(\text{post-period } 2, \text{ring} = r, \text{time} = m) + \\
\mathbf{X}\boldsymbol{\beta} + \lambda_t + \alpha_{location(i)} + \varepsilon_{it} \qquad (4)
\end{aligned}
$$

Where $\mathbb{1}(\text{ring} = r)$ is an indicator variable for property i belonging to ring r, for $r \in 1, 2, 3$; $\mathbb{1}(\text{time} = m)$ is an indicator variable for unit i belonging to tercile m of off-freeway driving time. γ_{jrm} captures the average treatment effect in post-period $j \in \{1, 2\}$ for properties belonging to ring r and the accessibility tercile m.

Figure 8: Accessibility

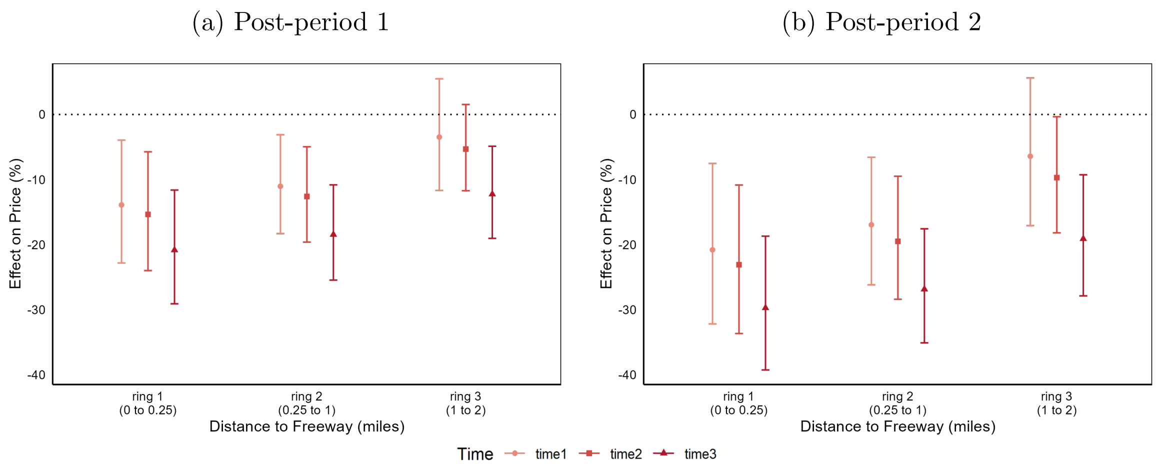


Notes: The map shows average driving times to and from Loop 202 South Mountain Freeway in both directions, highlighting the variability in accessibility gains for properties located at the same distance from the freeway. Consequently, properties with similar exposure to disamenities may experience different accessibility gains due to driving time differences.

Results

Figure 9 plots the treatment effect for each combination of accessibility and disamenity bins. As in previous sections, we can see an anticipatory effect in panel (a) in the pre-opening period. As panel (b) shows, the effects are larger in absolute terms in the post-opening period. In both panels, the treatment effects become more negative within the same disamenity level (same ring) as accessibility gains decrease (darker colors). This pattern is repeated across the board. Similarly, for a given level of accessibility gains (same color), the effects attenuate as one moves away from the freeway, and the exposure to disamenities decreases (higher ring).

Figure 9: Accessibility Gains and Disamenities



Notes: The figure displays the average treatment effect on the treated (ATT) on prices in each post-period across different combinations of distances from the freeway and driving times. The effect is calculated as $(e^{\gamma} - 1) * 100$ where γ is the OLS estimates for γ_{1rm} and γ_{2rm} from Equation 4 in panels (a) and (b), respectively. Note that γ_{2rm} reflects the total effect since the start of the treatment. The inner symbols indicate the point estimates, while the outer lines denote the 95% confidence intervals, calculated using standard errors clustered at the block group level. When moving from left to right while keeping accessibility gains constant (same symbol), the treatment effects diminish as the distance from the freeway increases, reflecting reduced exposure to disamenities. Conversely, when moving from right to left while keeping exposure to disamenities constant (within the same ring), the treatment effects attenuate as driving time decreases, capturing greater accessibility gains.

Notably, when comparing properties with similar exposure to disamenities (within the same ring), the treatment effects can attenuate by up to 12.69 p.p. due to differences in accessibility gains. For instance, properties in the third ring—located 1 to 2 miles from the freeway—accumulate a negative capitalization effect of 19.11% if they fall within the third tercile of accessibility, while the effect is reduced to 6.42% for those in the first tercile.

As an alternative strategy, in Appendix , I assume a functional form for the relation between housing prices and the variables capturing accessibility gains and freeway disamenities. This allows me to estimate treatment effects continuously on both variables, which gives similar results. I use this feature in Section 6 to analyze alternative scenarios.

Compound Measure

Alternatively, we can define a compound measure for treatment doses based on the accessibility gains and exposure to disamenities for each home. Let define the ratio $dose_i \equiv dist_i/time_i$ as the treatment dose and estimate the following model:

$$\begin{aligned}
\ln price_{it} = \beta_0 &+ \beta_{treated}\mathbb{1}(treated) + \gamma_{10}\mathbb{1}(post\text{-}period\ 1)\mathbb{1}(treated) + \\
&+ \gamma_{1d}\ dose_i\ \mathbb{1}(post\text{-}period\ 1)\mathbb{1}(treated) + \\
&+ \gamma_{20}\mathbb{1}(post\text{-}period\ 2)\mathbb{1}(treated) + \\
&+ \gamma_{2d}\ dose_i\ \mathbb{1}(post\text{-}period\ 2)\mathbb{1}(treated) + \\
&+ \mathbf{X}\boldsymbol{\beta} + \lambda_t + \alpha_{location(i)} + \varepsilon_{it}. \qquad (5)
\end{aligned}$$

Note that the dose ratio increases with distance from the freeway and decreases with driving time from the freeway. Accordingly, I expect it to correlate positively with accessibility and negatively with disamenities. Therefore, I expect a higher capitalization for homes with a higher ratio.

Table H1 in the appendix shows the estimates of Equation 5, which are in line with the expected results. The positive estimates for the interaction of $post_t \times treated_i \times dose_i$ show that the capitalization effect increases with the dose ratio, as expected. The further from the freeway and the shorter the driving time from the freeway, the better. Additionally, the positive estimates during post-period 1 reinforce that there is an anticipation effect that correlates with the dose ratio as expected.

Accumulated Capitalization

To illustrate the aggregate impact of the freeway on nearby housing values, I conduct a back-of-the-envelope calculation. Multiplying the estimated capitalization effect for each property by its initial price (in constant dollars) yields the implied change in property value attributable to the freeway. Summing these changes across all treated properties offers an indicative measure of the total capitalization cost in dollar terms.

The results suggest a permanent loss in property value of at least \$1.4 billion (in 2010 dollars). This figure excludes properties within the treated region that are not present in the dataset because they were not transacted during the study period. The implied capitalization cost represents roughly three-quarters (73.7%) of the direct expenditure reported by ADOT for the construction of the freeway (\$1.9 billion in 2010 dollars) (ADOT, 2024b). Compared to the economic benefits predicted by the DEIS in terms of time savings (\$3 billion in 2010 dollars), the capitalization cost offsets almost half of it (47%) (ADOT, 2020).

This aggregate computation should be interpreted with caution. Because it is based on DiD estimates, it reflects relative differences in housing prices between treated and control areas rather than total price changes over time. Accordingly, it abstracts from common growth in property values that affects both regions. The resulting figure should therefore be seen as an illustrative measure of the differential capitalization effect on nearby properties attributable to the freeway, not as a precise welfare measure or a comprehensive accounting of general equilibrium effects.

5 Identification

Placebo Test

One concern in causal inference studies is whether estimates are affected by unobserved confounders. In this case, broader changes to roadway traffic across the city during this period could have affected the observed capitalization changes rather than L-202 SM alone. To address this, I examine properties near other freeways within the metropolitan area.

As a placebo test for the capitalization effect of L-202 SM, Table 3 presents the estimated effects on properties near other freeways within the area. These houses are unaffected by local amenities of L-202 SM, but would be affected by any general change related to roadway traffic. For each freeway, I estimate Equation 1, defining treated units as properties within 2 miles of the respective freeway and control units as those located between 3 and 5 miles away, following the guidelines outlined in Section 3.1.

All point estimates in the placebo tests, shown in Columns (2) to (6) of Table 3, are less than one-third of the estimates for the treated properties in Column (1), and none are statistically distinguishable from zero at the 5% level. As expected, properties near other freeways do not exhibit similar effects to those observed for properties near L-202 SM. However, some capitalization effects may occur if L-202 SM enhances accessibility by expanding the freeway network (Klaiber and Smith, 2010). This could be the case for properties near the L202 San Tan Freeway (L202-ST) in Column (6), as L-202 SM extends L202-ST to the northwest, potentially enhancing connectivity for properties west of the Valley. Alternatively, there may be some capitalization effect if L-202 SM effectively diverts traffic in the West-East orientation from I-10 and I-17. This could be the case in Columns (3) and (4). Nonetheless, the increased exposure to disamenities due to higher traffic volumes could offset these accessibility gains. Ultimately, the key takeaway from Table 3 is that there are no capitalization effects in the placebo tests comparable to those estimated for the treated properties.

Table 3: Placebo Test

	Dependent variable: ln Price					
	(1)	(2)	(3)	(4)	(5)	(6)
	L-202 SM Treated	I-10 NS Placebo	I-10 WE Placebo	I-17 Placebo	L-202 RM Placebo	L-202 ST Placebo
Post-period 1	-0.1286***	-0.0157	0.0441	0.0314	-0.0065	0.0246*
	(0.0338)	(0.0290)	(0.0286)	(0.0244)	(0.0249)	(0.0135)
Post-period 2	-0.2200***	-0.0178	0.0647	0.0595*	-0.0160	0.0317*
	(0.0471)	(0.0425)	(0.0409)	(0.0335)	(0.0322)	(0.0183)
Housing Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Spatial FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,422	64,632	109,509	128,355	93,740	128,250
R^2	0.90049	0.83827	0.86649	0.87001	0.88056	0.90778

Notes: The table presents OLS estimates from Equation 1. Note that γ_2 captures the total effect since the start of the treatment. Column (1) reports the baseline result, while Columns (2) to (6) show placebo tests conducted on other freeways in the Valley. All point estimates in the placebo tests are less than one-third of the estimates in Column (1), and none is statistically different from zero at the 5% significance level. These findings confirm that the placebo test performed as expected, as there is no reason to anticipate similar effects on properties near other freeways compared to those near L-202 SM. Housing controls include livable area, presence of a pool, lot size, number of bathroom fixtures, and house age. Standard errors are clustered at the block group level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

5.1 Specific Threats to Identification

Parallel Trends

The identification strategy relies on the assumption of parallel trends. Testing whether it holds is not possible. However, examining pre-period trends for supportive evidence is standard practice. This section provides evidence supporting parallel pre-trends.

First, Figure 4 suggested the presence of parallel trends in raw data in the pre-period. Second, the event study plot in Figure 5 allows for statistical tests for the joint nullity of the pre-period coefficients when controlling for covariates. As mentioned before, I cannot reject joint nullity in the pre-test. The p-value for the Wald test is 0.33. This suggestive evidence supports the parallel trend assumption required for the DiD estimator to identify the average treatment effects on the treated.[29] Figure M1 provides additional support by showing that trends in price changes have remained similar over the past two decades, even with the mortgage crisis that occurred in this period.

Another potential concern is whether the distance from the control region lies sufficiently far from the freeway to be unaffected by spillovers. In particular, whether treatment effects might extend beyond the treated ring and affect the control ring. To assess this, I perform a robustness check on whether treatment effects become null when moving away from the freeway before reaching the control ring. I estimate treatment effects for two additional rings placed within the buffer. As shown in Figure 6, the estimated effects decline monotonically with distance from the freeway and become statistically indistinguishable from zero within the buffer (Rings 4 and 5), well before reaching the control ring. In a complementary exercise, I divide the control ring into two halves and perform a DiD using the inner half (Ring 6) as a treated group and

[29] The problems noted by the recent literature (e.g. Goodman-Bacon (2021) or De Chaisemartin and d'Haultfoeuille (2020)) relative to weights on the estimator and possible negative weights in the average treatment effect could arise in the presence of differential treatment timing. This is not the case in this paper since all the treated units are treated simultaneously. There are no multiple treated groups. Thus, the control group is always non-treated. The problematic case when the control is already treated is absent here. Nevertheless, I apply a Bacon decomposition, which gives one comparison (treated vs untreated) with weight one, and DCdH decomposition, which gives 41 ATTs, corresponding to each quarter, all receive a positive weight.

the outer half (Ring 7) as a control. If the treatment effects extend over the control ring then one should expect a larger effect on the inner half, given the fade-out pattern observed in Figure 6. In contrast, Table J1 in the appendix shows that the treatment effect is null in the inner half of the control ring.

These robustness exercises show that treatment effects are negative close to the freeway, converge to nullity when moving away, and remain stable at zero within the control ring. Moreover, the effect is not statistically different from zero within the buffer. Thus, these robustness exercises support my definition of both rings, treated and control.

Freeway Overlapping

Another threat to identification would be a SUTVA violation caused by an indirect effect of L-202 SM on other freeways. As discussed before, L-202 SM could affect the traffic in connected or substitute freeways, affecting their disamenities. Also, it can affect the capitalization of preexisting freeways by accessibility gains from an extended roadway network. Alternatively, the effect of a new nearby freeway could be different if it is the first one for properties exposed to preexisting freeways. I address these concerns by analyzing whether the results are robust to removing properties that could be affected by other freeways. Table M1 in the appendix reports the estimates of Equation 1 removing properties within 2 miles of another freeway than L-202 SM. It shows that the results are robust. The point estimates for post-period 1 and 2 change only 8% and 13%, respectively.

Supply Reaction

A supply expansion could be another potential cofounder for estimating a negative effect on prices. The new freeway could lead to relatively more new developments nearby. Table I1 in the appendix provides evidence against this hypothesis by showing that the age of properties sold in the treated region is not lower than those in the control region after the freeway was announced and once in place. If there were more new housing developments in the treated region, one would expect to see a higher proportion of younger properties sold in this region, and this is not the case. Table I2 reinforces this observation, showing there are no treatment effects on the age of sold properties.

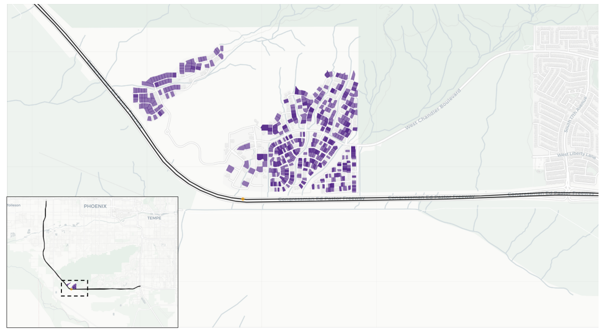
Furthermore, if the negative effect was explained exclusively by a shift in supply, in the classical diagram of price and quantity, one expects to see a new equilibrium at a lower price and higher quantity along the same demand curve. Table I3 in the appendix shows this is not the case. There is no positive effect on quantities.

Mobility Changes

There is an additional feature that requires consideration. The Covid-19 pandemic spread 3 months after the freeway opened. This is an aggregate shock; thus, there is no reason to think it can affect the control and treated units differently. Moreover, both groups have evolved similarly for many years, experiencing ups and downs, as Figure M1 in the appendix depicts. Remarkably, their trends did not diverge radically even during the mortgage crisis.

However, traffic changes due to social distancing policies could be a cofounder for the estimated treatment effects. The concern is whether it had a differential impact on treated properties. Given the substantial changes in mobility during COVID, any such differential effect would likely be large. Figure M2 plots the quarterly ATT, as in Figure 5, and also includes Covid cases and deaths on the same time axis. The figure shows no response of the treatment effect to large changes in cases and deaths. While there appears to be a small jump around quarter 35, it dissipates in the following quarter and can reasonably be considered noise. The quarterly ATT remained stable since before the Covid-19 pandemic could be foreseen, suggesting it is not a cofounder for the estimated treatment effects.

Figure 10: Additional Ramp



Notes: The figure shows the location of the simulated additional ramp and the properties that would experience improved accessibility as a result. Although only 2.46% of the treated properties are impacted by this policy, the effect is substantial, amounting to $58 million in 2010 dollars.

6 Alternative Scenarios

6.1 Additional Ramp

In this exercise, I analyze the capitalization of including an extra ramp in the Southwest of L-202 SM near the most affected properties, those close to the freeway but far from any ramp. These properties can be distinguished in Figure 8 as the ones with a high driving time and low distance showing the largest negative effects in Figure G1a.

The additional ramp reduces the driving time for properties using further ramps. I simulate the driving time to/from the additional ramp and compare it to the fastest observed driving time.[30] Figure 10 shows the additional ramp location and those properties that would enjoy accessibility gains from this additional ramp.

Table 4 summarizes the capitalization of the extra ramp. Although only 2.46% of the treated properties are affected by this policy, the impact is sizeable, $58 Million in 2010 dollars. This large figure has two main drivers: affected properties have a higher price than the median treated property, and given that the actual driving time is large,

[30] I assume driving time on roads along the route to/from the freeway stays the same with the additional ramp. This means assuming either that the traffic increase on these roads would be minor and not generate delays or that the new ramp includes improvements that compensate for the traffic increase. Moreover, I ignore any impact on driving time along the freeway. If any, it would affect the accessibility gains from the freeway for all properties.

Table 4: Additional Ramp

	Aditional Ramp
Affected properties (#)	457
Affected properties (%)	2.46
Median price of aff. prop. (2010 $)	564,790
Median change (p.p.)	12.69
Accumulated change (2010 $)	58,406,897

Notes: The table summarizes the results of the exercise of adding an additional ramp near the most negatively impacted properties. Although only 2.46% of the treated properties are affected by this policy, the impact is significant, totaling $58 million in 2010 dollars. The improved accessibility from the extra ramp leads to an additional capitalization of 12.69 percentage points in the median for the 457 affected properties.

so is its reduction with the new ramp and the consequent change in the capitalization.

The capitalization gains for building this new ramp are likely to increase further because there are new planned housing developments in this location that would use the new ramp (News, 2024; Axios, 2024). Of course, a comprehensive evaluation would also require information about the cost of an additional ramp.

However, an approximation can be made from ADOT's estimates for similar projects. For example, a two-way ramp at I-19 and Ruby Road was estimated to cost $13 million in 2010 dollars (ADOT, 2018). The estimated cost for an interchange at I-10 and Baseline Road ranges from $22 million to $56 million in 2010 dollars, depending on whether a modified or diverging diamond interchange is constructed (ADOT, 2024a). Additionally, a Loop 101 to 91st Avenue ramp connector is estimated at $33 million in 2010 dollars (ADOT, 2022). While these estimates vary widely, they suggest that the capitalization benefits of adding an extra ramp to L-202 SM seem to outweigh its estimated construction cost.

The reader should notice that this back-of-the-envelope calculation is subject to the same caveats mentioned above. The resulting figure should be seen as an illustrative measure of the differential capitalization effect on nearby properties attributable to the freeway, not as a precise welfare measure or a comprehensive accounting of general equilibrium effects. A precise welfare evaluation of the ramp addition, which is not the purpose of this exercise, would require a model explicitly accounting also for endogenous congestion effects.[31]

Nevertheless, this exercise demonstrates the importance of ramp location choice for roadway capitalization effects. For example, the addition of an extra ramp could significantly shift the freeway's distributional consequences of the project.

6.2 Alternative Location

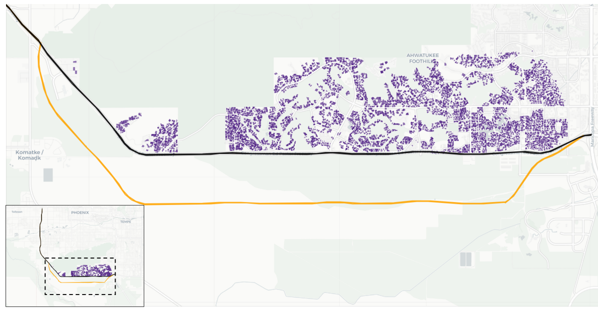
In this exercise, I compare the actual capitalization of the freeway to that of an hypothetical freeway in an alternative location within native land, further from properties in the South. A group of GRIC residents proposed this alternative location once ADOT decided to build the freeway despite opposition to placing it on native land.[32] They proposed this location as a way to limit externalities, but it was rejected, and L-202 SM was placed as announced. Figure 11 shows current and alternative L-202 SM and affected properties.

The alternative location changes driving times and distance from the freeway for treated houses along the Southern segment. I assume the portion of native land between actual and alternative freeways remains undeveloped, which seems reasonable given that it is inside GRIC and its residents have already opposed urbanization on native land. In

[31]In this specific scenario, any potential increase in congestion due to the additional ramp is expected to be marginal. The alternative under consideration involves the addition of only one extra ramp, located roughly 2 miles from the nearest existing one. The situation would differ if multiple segments of the freeway were modified, creating a cluster of ramps; in that case, vehicles entering through one ramp could exit soon after through another, potentially increasing congestion. This is not the case here. Moreover, the number of households for whom this new ramp would be the nearest is limited (approximately 500). These households currently access the freeway through the adjacent ramp, so the new ramp would primarily redistribute existing traffic rather than generate new freeway users. Therefore, given that the new ramp is distant from others and unlikely to attract additional traffic, its impact on congestion should be limited and can reasonably be considered negligible.

[32]As mentioned in Section 2.1, ADOT originally planned to place the freeway in the native land of GRIC. However, GRIC residents opposed to the freeway. After unsuccessful attempts to achieve a negotiated solution, ADOT decided to build the freeway anyway and place it out of native land. It implied blasting part of the South Mountain, which GRIC considers sacred. As a counterproposal, a group of residents try to avoid blasting South Mountain and accept that part of L-202 SM go across native land. This is the alternative placement analyzed in this exercise.

Figure 11: Alternative Location



Notes: The figure indicates the freeway placement in the alternative scenario and the properties affected by the change. While accessibility gains are reduced with the proposed placement, disamenities also decrease, as the freeway is placed further away from the properties.

order to compute driving times, I assume the route between the actual and alternative ramps is a straight line and that the travel speed is the same as that of roads connecting ramps. The straight line assumption is consistent with assuming native land remains undeveloped. The speed assumption is conservative. Given that this land remains undeveloped, it is reasonable to think that road speed would be somewhere between that of minor roads and the freeway.

Table 5 summarizes changes in capitalization due to the alternative placement. This scenario relocates a large portion of the freeway and affects 52.04% of treated properties. The alternative location moves the freeway away from properties. Thus, it reduces their exposure to disamenities. However, it also reduces accessibility due to longer trips to connect the freeway. Therefore, the net effect is uncertain ex-ante.

Table 5 shows that reductions in exposure to disamenities outweigh the effect of the reduction in accessibility gains for the median property. The off-freeway driving time increases by a minute, and the alternative location moves the freeway 1 mile away from properties. It is worth noting that there is a reduction in accessibility gains for all the properties. The alternative placement increases the in-freeway driving time along the Southern segment. Moreover, it increases the off-freeway driving time when using any Southern ramp. This exercise ignores both effects. Therefore, it should be read as an

Table 5: Alternative Location

	Alt. Location
Affected properties (#)	9,654
Affected properties (%)	52.04
Median price of aff. prop. ($)	433,804
Median change (p.p.)	11.78
Accumulated change (2010 $)	829,307,528

Notes: The table summarizes the results of the exercise of relocating the Loop 202 South Mountain Freeway. While accessibility gains diminish with the proposed placement, disamenities also decrease as the freeway is placed farther from the properties. A total of 52.04% of the treated properties are affected by this policy, resulting in accumulated capitalization effects of $829 million in 2010 dollars. The new location mitigates the negative impact of the freeway, reducing it by 11.78 percentage points in the median.

upper bound for the capitalization changes.[33]

In spite of the sizeable gains in capitalization, a comprehensive evaluation of the alternative location should consider changes in costs. As a first approximation, a back-of-the-envelope calculation for the average per-mile construction cost can be extrapolated to the additional freeway length. The total construction cost of $1.9 billion in 2010 dollars, divided by the 22 miles of length, leads to a per-mile average cost of $87 million in 2010 dollars. Therefore, the additional 1.28 miles would cost $111 million in 2010 dollars if the marginal cost per mile is equal to the average cost. This rough calculation suggests the capitalization benefits would have exceeded the construction cost of this alternative placement by a factor of 8-to-1. However, additional factors should be considered for a comprehensive evaluation.

On the one hand, the larger extension of the freeway would increase costs in terms of time use through longer driving time, in addition to construction costs. On the other hand, the alternative location would have avoided the cost of blasting part of

[33]This exercise does not account for potential impacts on properties within native land that could be exposed to traffic disamenities under the alternative alignment. Data limitations prevent a full assessment, but at most four designated places within the Gila River Indian Reservation (Maricopa Colony, St. Johns, Komatke, and Gila Crossing) could be partially affected. Together, they contain 1,987 housing units, as reported in the 2020 Census. Even under conservative assumptions, any adverse impacts on these properties would not offset the estimated gains for the properties analyzed.

South Mountain. Therefore, it is not straightforward to perform an exhaustive cost-benefit analysis of this policy, and it exceeds the scope of this paper. The takeaway for policy is that extending a planned roadway could reduce accessibility gains and increase construction expenditure, but also generate much larger capitalization benefits.

Beyond the idiosyncratic characteristics of this particular setting, the results of the alternative scenarios highlight the importance of engineering decisions in the construction of transportation infrastructure. Variations in roadway placement can substantially alter capitalization effects. Even subtle adjustments, such as the location of a ramp, can lead to substantial changes in capitalization. Similarly, other technical features of transportation projects influencing accessibility gains and exposure to disamenities may have meaningful capitalization effects.

7 Conclusion

This paper analyses the capitalization of new freeway infrastructure, a large-scale place-based intervention. These projects create a fundamental local trade-off, providing accessibility gains while simultaneously generating localized disamenities. Using the 2019 opening of the Loop 202 South Mountain Freeway as a natural experiment, I find that the net effect on nearby single-family properties was large and negative. Prices fell by 12% in anticipation of the freeway and deepened to a stable, 20% decline after it opened. These findings show that for proximate households, the perceived and realized disamenity costs can substantially outweigh the accessibility benefits.

This paper's primary contribution is to decompose this net effect. By exploiting the differential spatial scales on which accessibility—shifted by ramp access—and disamenities—shifted by freeway proximity—operate, I am able to separately identify these two opposing channels. I find that while the disamenity effect is strongly negative, the accessibility gains are substantial and can mitigate the capitalization loss by more than half for properties better connected to the freeway.

Back-of-the-envelope calculations suggest a total capitalization loss of almost one-half of the predicted $3 billion economic benefits of the project in terms of time savings. Crucially, my results suggest that these impacts can be largely affected by design choices. The simulated alternative scenarios show that engineering decisions, such as freeway alignment or ramp location, can substantially shape local capitalization effects and, in turn, their distributional impact on household wealth. Future research could further unbundle the specific disamenity channels and track the long-run sorting of households in response to these powerful, localized effects.

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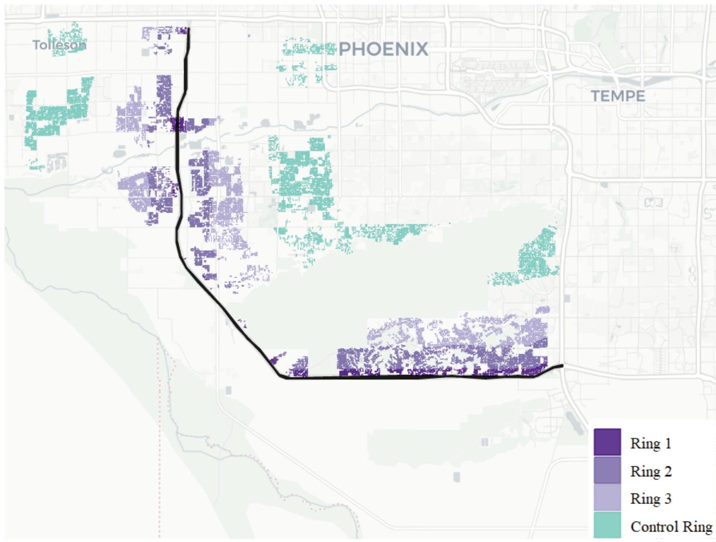
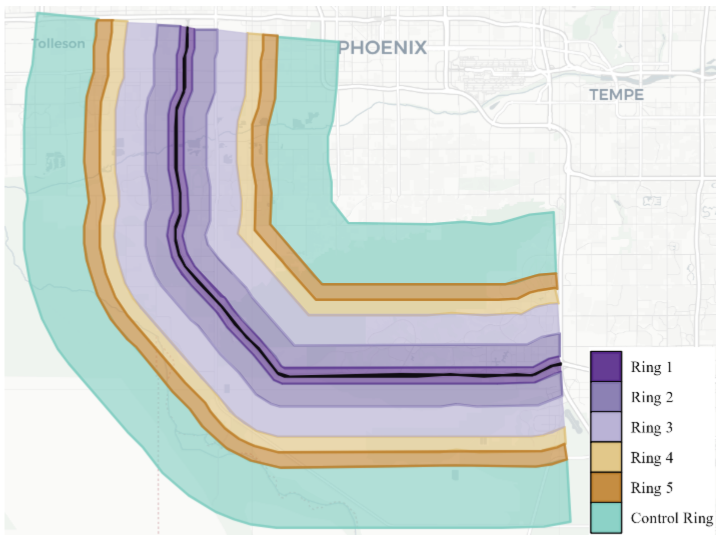
A Maps

Figure A1: Treated and Control Units



Notes: The map illustrates the empirical design, showing the units involved in the analysis. Treated units are colored in violet, while control units are shown in green, with the Loop 202 South Mountain Freeway depicted in black. Rings represent subsets of the treated group, categorized by proximity to the freeway. The union of the violet units corresponds to the treated units described in Section 3.1. Properties within 0.25 miles of the freeway are part of Ring 1, those between 0.25 and 1 mile are in Ring 2, and those between 1 and 2 miles are in Ring 3. The buffer region lies between 2 and 3 miles from the freeway, and the control region extends from 3 to 5 miles.

Figure A2: Treated, Buffer and Control Regions



Notes: The map illustrates the empirical design, displaying the theoretical definition of regions. All units within a region are assigned to the corresponding group. The treated rings are colored in violet, the control region in green, and the buffer region in yellow. The union of the violet regions represents the treated ring. The treated rings are subsets of the treated region, defined by their proximity to the freeway. Properties within 0.25 miles of the freeway are in Ring 1, those between 0.25 and 1 mile are in Ring 2, and those between 1 and 2 miles are in Ring 3. The buffer region is further divided into two additional rings: Ring 4 spans 2 to 2.5 miles from the freeway, and Ring 5 covers 2.5 to 3 miles. The control region extends from 3 to 5 miles from the freeway. The Loop 202 South Mountain Freeway is depicted in black.

B Descriptive Statistics

Table B1: Descriptive Statistics: Control and Treated Group

	Before announc. Jan2011-Mar2015	After announc. Apr2015-Dec2019	After opening Jan2020 onward
Num. of Properties			
Control	2,971	7,295	3,780
Treated	4,963	12,195	6,046
Livable Area (Sq. Ft.)			
Control	1,902	1,928	1,961
Treated	2,171	2,134	2,146
Lot Size (Sq. Ft.)			
Control	7,266	7,360	7,409
Treated	7,618	7,357	7,500
House Age			
Control	12.44	17.77	22.12
Treated	11.41	16.24	21.14
Num. of Bathroom Fixtures			
Control	7.71	7.73	7.88
Treated	9.09	9.05	9.09
Pool (%)			
Control	16.16	16.36	16.78
Treated	35.60	36.89	39.29

Notes: The table reports the number of properties sold, mean livable area in squared feet, mean lot size in squared feet, mean house age in years, mean number of bathroom fixtures, and percentage of transactions involving a unit with pool of the transactions that occurred in the pre-period, post-period 1, and post-period 2 for treated and control group.

Table B2: Descriptive Statistics: Control and Rings

	Before Announc. Jan2011-Mar2015	After Announc. Apr2015-Dec2019	After Opening Jan2020 onward
Properties			
Control	2,971	7,295	3,780
Ring 1	509	1,396	785
Ring 2	2,130	5,291	2,594
Ring 3	2,324	5,508	2,667
Livable Area (Sq. Ft.)			
Control	1,902	1,928	1,961
Ring 1	2,055	2,107	2,101
Ring 2	2,160	2,112	2,132
Ring 3	2,208	2,164	2,173
Lot Size (Sq. Ft.)			
Control	7,266	7,360	7,409
Ring 1	6,602	6,521	6,544
Ring 2	7,661	7,355	7,453
Ring 3	7,810	7,578	7,828
House Age			
Control	12.44	17.77	22.12
Ring 1	14.47	18.49	22.38
Ring 2	12.11	17.34	22.23
Ring 3	10.08	14.57	19.72
Num. of Bathroom Fixtures			
Control	7.71	7.73	7.88
Ring 1	9.08	9.40	9.40
Ring 2	9.14	9.03	9.14
Ring 3	9.06	8.97	8.94
Pool (%)			
Control	16.16	16.36	16.78
Ring 1	46.41	48.66	45.90
Ring 2	37.37	39.02	41.66
Ring 3	31.52	31.72	35.01

Notes: The table reports the number of properties sold, mean livable area in squared feet, mean lot size in squared feet, mean house age in years, mean number of bathroom fixtures, and percentage of transactions involving a unit with pool of the transactions occurred in the pre-period, post-period 1, and post-period 2 for control and treated groups. Rings are subsets of the treated group defined by proximity to the freeway. Units within 0.25 miles of the freeway are Ring 1, between 0.25 miles and 1 mile from the freeway are Ring 2, and between 1 mile and 2 miles from the freeway are Ring 3.

C Access to Major Employment Centers

Table C1: South Mountain Freeway in the Optimal Route to Major Employment Centers

Group	Control (%)	Treated (%)
Central Phoenix	0.50	50.55
Camelback	0.50	53.92
Encanto	0.50	54.02
Scottsdale (downtown)	0.50	53.92
Mesa	0.50	51.14
Tempe	0.50	45.43
Scottsdale (North)	0.50	69.87
Any major employment center	0.50	69.87

Notes: The table reports the percentage of treated and control properties for which the Loop 202 South Mountain Freeway is part of the shortest-time route to the major employment centers identified by Ahlfeldt et al. (2025).

Table C2: Driving times to freeway and prime locations

	Dependent variable: Average driving time to prime locations		
	(1)	(2)	(3)
Time to L-202 SM	0.5466***	1.206***	1.237***
	(0.0858)	(0.1128)	(0.1679)
Miles to L-202 SM		-1.823***	-1.776***
		(0.2672)	(0.3976)
Spatial FE	Yes	Yes	Yes
Sample	Treated and Control	Treated and Control	Treated
Observations	29,273	29,273	18,241
R^2	0.97597	0.97951	0.96798
Within R^2	0.25665	0.36607	0.38041

Notes: The table presents OLS estimates of driving time to South Mountain Freeway explaining average driving time to prime locations in Phoenix metropolitan area defined by Ahlfeldt et al. (2025). Column (1) includes only a constant term. Column (2) incorporates spatial fixed effects, while Column (3) controls also for distance to the freeway. Column (4) restricts the sample to treated properties only. Standard errors are clustered at the block group level when controlling for spatial fixed effects.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

D Demographics

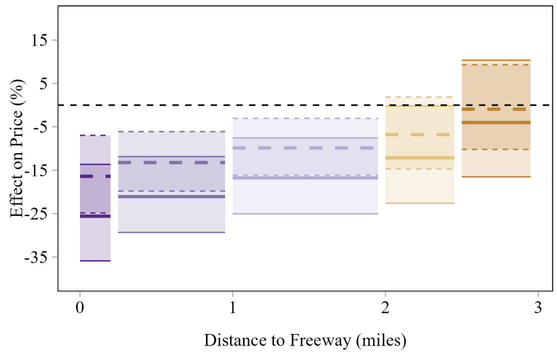
Table D1: Demographics characteristics in the analyzed region

Group	Year	Income	White (%)	Some college (%)	Age	Household w/children (%)
Control	2013	52,777	73.54	47.33	31.04	43.34
Control	2020	68,863	61.68	53.55	32.84	42.02
Treated	2013	79,235	75.35	70.94	33.18	45.14
Treated	2020	91,094	65.71	66.35	34.14	44.91
Control	2020-2013 (pp)		-11.86	6.21		-1.31
Treated	2020-2013 (pp)		-9.64	-4.60		-0.23
Control	2020-2013 (log)	0.27			0.06	
Treated	2020-2013 (log)	0.14			0.03	
Treated - Control	2020-2013 (pp)		2.22	-10.81		1.08
Treated - Control	2020-2013 (log)	-0.13			-0.03	

Source: ACS. *Notes*: Block groups which overlap with treated and control region.

E Anticipated and Total Effects

Figure E1: Anticipated and Total Effects by Distance from the Freeway



Notes: The figure displays the average treatment effect on the treated (ATT) on prices both post-period across varying distances from the freeway. The effect is calculated as $(e^{\gamma} - 1) * 100$ where γ is the OLS estimates for γ_{1r} and γ_{2r} from Equation 3. Note that γ_{tr} for $t \in \{1, 2\}$ are both plotted on top of each other and reflect the total effect since the start of the treatment until the end of post-period t. The inner lines represent the point estimates, while the outer lines denote the 95% confidence intervals based on standard errors clustered at the block group level. Figure A2 shows these regions.

F Price as Future Rents Flow

The path of cumulative effects on log(price) could be seen as changes in the present value of the future flows of rents, which step down by a constant amount each quarter up to T^* (freeway opening) and are full-adjusted thereafter. Then, the per-quarter discount factor $\beta = 1/(1+r)$ makes the present value accumulate geometrically up to T^*.

If L denotes the long-run log price effect (defined by the average of $t \geq 27$ coefficients; 0.2112). With the constant per-quarter discount factor, the event-study path should follow

$$\gamma_t \approx L \frac{1-\beta^{\min(t,T^*)}}{1-\beta^{T^*}} \quad \text{for } t \geq 0,$$

and $\gamma_t \approx 0$ for $t < 0/$

Then, β is estimated by weighted non-linear least squares as

$$\hat{\beta} = \underset{\beta \in (0,1)}{\arg\min} \sum_{t=0}^{T^*} \frac{1}{se_t^2} \left[\gamma_t - L \frac{1-\beta^t}{1-\beta^{T^*}} \right]^2 .$$

The estimated quarterly coefficient, $\hat{\beta}$, can be translated into a quarterly interest rate $r^q = \hat{\beta}^{-1} - 1$, which can then be converted to an annual rate, $r^a = (1 - r^q)^4 - 1$. This corresponds to an annual implicit interest rate of 9.74%. The implied spread of 5.7 percentage points relative to the average 30-year fixed mortgage rate in the United States during the same period (4.04%) appears reasonable and supports the plausibility of the asset-pricing hypothesis as one component of the anticipation effect. Other mechanisms, such as learning or construction-related effects, may also help explain the estimated treatment effects observed before freeway completion and thus contribute to the observed spread.

G Exponential Decay Function

Following Brinkman and Lin (2022), I assume disamenities decay exponentially with distance from the freeway and use their estimate to parametrize its spatial attenuation. For accessibility, I assume a linear function in Equation 6.

$$\begin{aligned}
\ln price_{it} = \beta_0 + \beta_1 dist + \beta_2 time + \beta_{treated}\mathbb{1}(treated) + \gamma_{post*treated}\ \mathbb{1}(post * treated) + \\
+ \gamma_{post*treated,dist}\ e^{-\eta * dist}\ \mathbb{1}(post * treated) + \\
+ \gamma_{post*treated,time}\ time\ \mathbb{1}(post * treated) + \\
+ \mathbf{X}\boldsymbol{\beta} + \lambda_t + \alpha_{location(i)} + \varepsilon_{it}
\end{aligned} \tag{6}$$

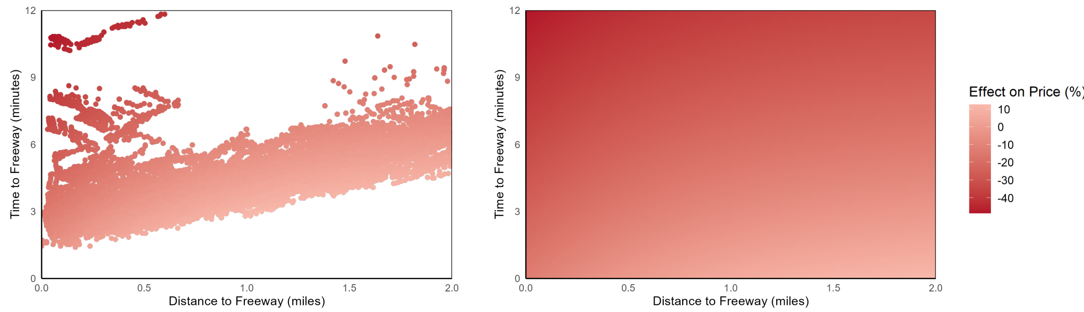
Where $dist$ is the distance from the freeway, $time$ is the average driving time from/to L-202 SM in both directions, and $\eta = 1.237$, estimated in Brinkman and Lin (2022).

Figure G1 shows estimates for the treatment effects on the treated properties, where $\hat{TT}_{i,dist,time} = \hat{\gamma}_{post*treated} + \hat{\gamma}_{post*treated,dist}\ e^{-\eta * dist} + \hat{\gamma}_{post*treated,time}\ time$. Figure G1a plots the treatment effects for each treated property, where the darker the dots, the more negative the effects. As expected, dots are lighter when moving away from the freeway (to the right in the plot) and to faster access (downward in the plot). Negative effects attenuate as the exposure to disamenities decreases and accessibility gains increase. The darker dots at the top left represent properties close to the freeway but with reduced accessibility gains. They are far from any ramp and must take long off-freeway trips. These properties are geographically concentrated and can be recognized in Figure 8 due to their high driving time. The exercise in Section 6.1 focuses on those properties and analyzes the effects of building an extra ramp close to them.

Figure G1b plots the result of computing the estimates for any distance and driving time combination. The largest negative effects (darker in the plot) are on those properties close to the freeway but with a long trip to the ramps. The negative effects

Figure G1: Continuous Treatment Effects

(a) Observed Properties (b) Potential Effect



Notes: The figure displays the treatment effect on the treated (TT) on property prices. Panel (a) shows the treatment effect on observed properties, while panel (b) presents the potential effect at any combination of driving time and distance from the freeway. The effect is calculated as $(exp(\gamma_{post*treated} + \gamma_{post*treated,dist}\ e^{-\eta*dist} + \gamma_{post*treated,time}\ time) - 1) * 100$ based on OLS estimates from Equation 6. Darker colors indicate larger negative effects. As expected, the dots become lighter as one moves farther from the freeway (to the right in the plot) and closer to faster access (downward in the plot). Negative effects diminish as exposure to disamenities decreases and accessibility gains increase. Notably, panel (a) shows that no properties are observed in the most favorable combination of large distance (lower disamenities) and short driving time to the freeway (higher accessibility gains).

attenuate and even become positive for those properties far from the freeway and with a short trip to the ramps.

The estimates from this section can inform a back-of-the-envelope calculation. The accumulated capitalization effect is at least \$1.4 billion in 2010 dollars. This calculation excludes properties in the treated region that are not in the dataset, as they were not sold during the study period. The capitalization cost is equivalent to almost three-quarters (73.68%) of the direct expenditure of constructing the freeway, \$1.9 billion in 2010 dollars.

In summary, the net capitalization effect of the new freeway nearby properties was negative. The negative effects increased gradually in absolute terms after the information was released, and they attenuated with distance from the freeway. Accessibility gains vary among properties depending on how fast households can travel to the nearest ramp, and differences in accessibility gains can attenuate the negative effect by more than half.

H Compound Measure Estimates

Table H1: Treatment Effects on House age

	Dependent variable: ln Price
Post-period 1	-0.2071***
	(0.0460)
Post-period 2	-0.3508***
	(0.0632)
Post-period 1 × doses	0.3782***
	(0.1292)
Post-period 2 × doses	0.6382***
	(0.1904)
Housing Controls	Yes
Time FE	Quarter-Year
Spatial FE	Yes
Observations	44,419
R^2	0.90154

Notes: The table reports OLS estimates of Equation 5. Housing controls include livable area, pool, lot size, number of bathrooms, and house age. Standard errors are clustered by census block group.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

I Transactions

Table I1: Descriptive Statistics: House age

	Before announc. Jan2011-Mar2015	After announc. Apr2015-Dec2019	After opening Jan2020 onward
Num. of Properties			
Control	2,971	7,295	3,780
Treated	4,963	12,195	6,046
House Age			
Control	12.24	16.94	21.46
Treated	11.38	16.05	21.23
Num. of Properties under 5 y.o.			
Control	906	1,463	622
Treated	914	1,323	324
Properties under 5 y.o. (%)			
Control	30.49	20.05	16.46
Treated	18.42	10.85	5.36
Num. of Properties under 1 y.o.			
Control	477	1,028	324
Treated	289	908	151
Properties under 1 y.o. (%)			
Control	16.06	14.09	8.57
Treated	5.82	7.45	2.50

Notes: The table reports the number of properties sold, mean house age in years, number of properties sold under 5 y.o., percentage of properties sold under 5 y.o., number of properties sold under 1 y.o., and percentage of properties sold under 1 y.o. for properties sold during the pre-period, post-period 1, and post-period 2 in the treated and control group.

Table I2: Treatment Effects on House age

	Dependent variable: Age
Post-period 1	−0.4221
	(0.5088)
Post-period 2	−0.3500
	(0.5932)
Housing Controls	Yes
Time FE	Quarter-Year
Observations	6,430
R^2	0.649

Notes: The table reports OLS estimates of Equation 1 using house age as LHS variable. Housing controls include livable area, pool, lot size, number of bathrooms, and house age. Standard errors are clustered by census block group.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table I3: Treatment Effects on Quantities

	Dependent variable: ln Transactions
Post-period 1	−0.015
	(0.053)
Post-period 2	−0.083
	(0.070)
Housing Controls	Yes
Time FE	Quarter-Year
Observations	6,430
R^2	0.649

Notes: The table reports OLS estimates of Equation 1 using $log(transactions)$ as LHS variable and block group as the unit of analysis. Housing controls include livable area, pool, lot size, number of bathrooms, and house age. Standard errors are clustered by census block group.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

J Control Ring

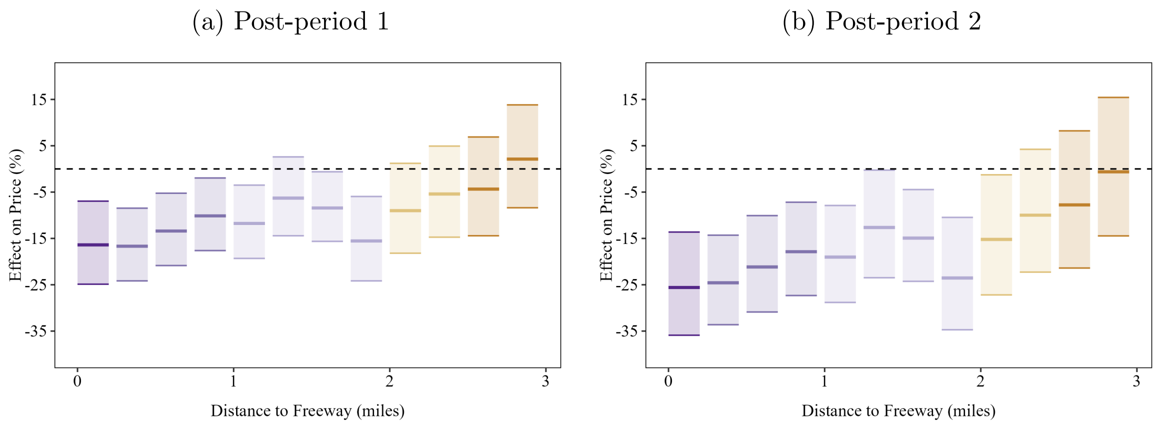
Table J1: Difference in Differences - Within Control Ring

	Dependent variable: ln Price	
	(1)	(2)
Treated*Treatment 1	0.009	0.0001
	(0.044)	(0.047)
Treated*Treatment 2	−0.021	−0.008
	(0.059)	(0.060)
Treated Group	Ring 6	Ring 6
Control Group	Ring 7	Ring 7
Time FE	Quarter-Year	Year (April to March)
Census Block Group FE	Yes	Yes
Property Characteristics	Yes	Yes
Observations	17,258	16,829
R^2	0.880	0.874
Adjusted R^2	0.879	0.873

Notes: The table reports OLS estimates of Equation 1 where the treated group is defined as the inner half of the original control group (Ring 6) and the Control Group is the outer half of the original control group (Ring 7). Standard errors are clustered by census block group. Property characteristics include: livable area, pool, lot size, number of bathrooms and house age.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

K Fine Spatial Heterogeneity

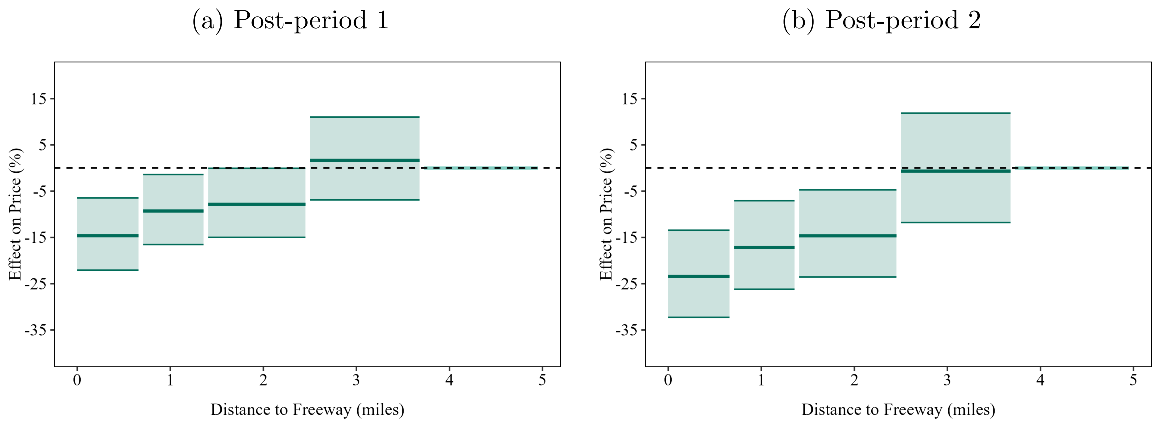
Figure K1: Heterogeneous Treatment Effects by Distance from the Freeway



Notes: The figure displays the average treatment effect on the treated (ATT) on prices in each post-period across varying distances from the freeway. The effect is calculated as $(e^{\gamma} - 1) * 100$ where γ is the OLS estimates for γ_{1r} and γ_{2r} from Equation 3 in panels (a) and (b), respectively. Different colors correspond to the rings shown in Figure 6. The smooth transition between rings indicates that the chosen intervals do not represent hard thresholds but rather serve as a useful reference for interpreting the results in line with evidence from other contexts. Note that γ_{2r} reflects the total effect since the start of the treatment. The inner lines represent the point estimates, while the outer lines denote the 95% confidence intervals based on standard errors clustered at the block group level. Figure A2 shows these regions.

L Alternative Partition

Figure L1: Partition by Distribution



Notes: The figure displays the average treatment effect on the treated (ATT) on prices in each post-period across varying distances from the freeway. The effect is calculated as $(e^{\gamma}-1)*100$ where γ is the OLS estimates for γ_{1r} and γ_{2r} from Equation 3 in panels (a) and (b), respectively. For an alternative definition of rings. Each ring corresponds to a quintile of distance from the freeway and the fifth quintile represents the control group. Quintiles is the optimal partition in the approach proposed by Cattaneo et al. (2024). The pattern of treatment effects is coherent with the estimates in Section 3.3. Note that γ_{2r} reflects the cumulative effect since the start of the treatment. The inner lines represent the point estimates, while the outer lines denote the 95% confidence intervals based on standard errors clustered at the block group level.

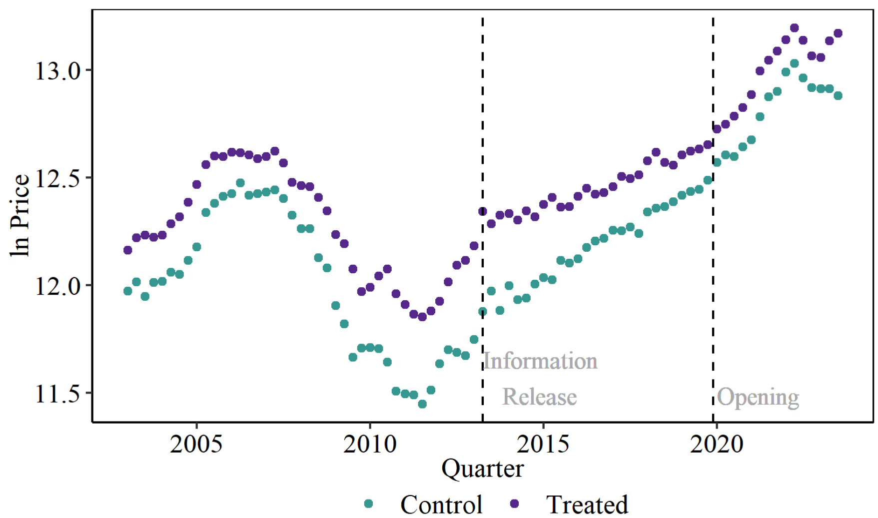
M Specific Threats to Identification

Table M1: Freeway Overlapping

	Dependent Variable: ln Price	
	(1)	(2)
Post-period 1	-0.1286***	-0.1181***
	(0.0338)	(0.0373)
Post-period 2	-0.2200***	-0.1908***
	(0.0471)	(0.0490)
Housing Controls	Yes	Yes
Time FE	Yes	Yes
Spatial FE	Yes	Yes
Observations	44,422	34,779
R^2	0.90049	0.91443

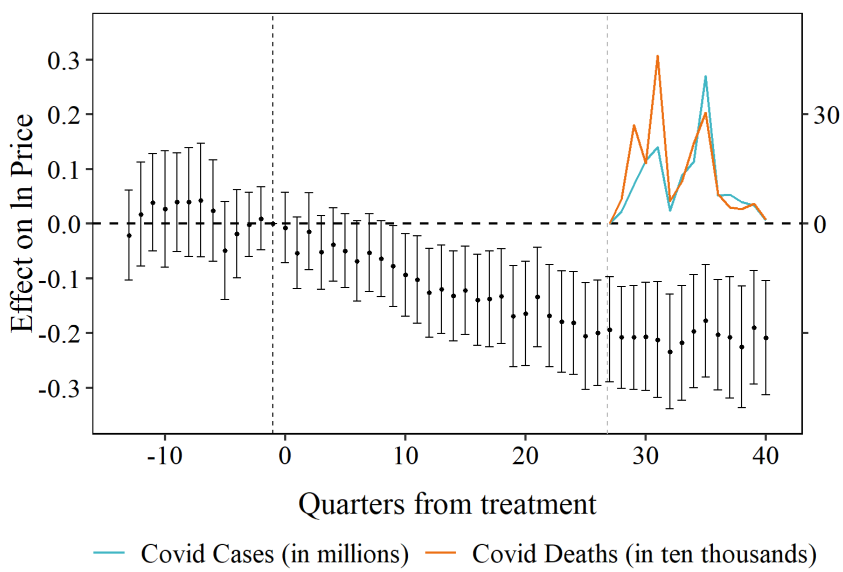
Notes: The table reports the estimates of Equation 1. Column (1) shows the baseline estimation for the whole sample, and Column (2) shows the baseline estimation removing properties within 2 miles of another freeway than L-202 SM. The estimates are similar showing the results are robust. Standard errors are clustered by census block group. Property characteristics include: livable area, presence of a pool, lot size, number of bathrooms and house age.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure M1: Raw Data - Long Run



Notes: Each dot represents the quarterly mean log-price of transactions for both the treated and control groups. Vertical lines indicate key events: the release of information and the freeway's opening. The treatment began in April 2013 when the Arizona Department of Transportation released the Draft Environmental Impact Statement, significantly increasing the likelihood of the freeway's construction. Post-period 1 concludes in December 2019, when the Loop 202 South Mountain Freeway officially opened to traffic. Post-period 2 extends from that point onward. Changes in price for the treated and control groups have not differed radically since the early 2000's, even during the mortgage crisis.

Figure M2: Treatment Effects and Covid-19



Notes: The dots represent OLS estimates for γ_t in Equation 2, capturing the average treatment effect on the treated (ATT) for the log of prices accumulated after t periods from the information release. The quarters on the x-axis are defined relative to the treatment start date (the information release in April 2013), with $t = -1$ serving as the reference category. The vertical dashed lines mark the boundaries between the two post-periods. The horizontal violet lines indicate the average ATT during each post-period. The bars represent 95% confidence intervals for each coefficient, with standard errors clustered at the block group level. On the right axis, the blue and orange lines represent the new COVID cases (in millions) and deaths for COVID-19 (in ten thousand) in each quarter. While both cases and deaths experienced notorious peaks, treatment effects did not respond. Quarterly ATT remained stable since before the Covid-19 pandemic could be foreseen, suggesting it is not a cofounder for the estimated treatment effects.

N Alternative Scenario Calculations

Results reported in Tables 4 and 5 are obtained by the following procedure. First, for each property, I re-compute driving times and distance from the freeway in each alternative scenario. Affected properties are defined as those for whom at least one of these variables are different than in the baseline scenario (actual freeway). Second, I re-compute the capitalization effect on each property using the estimates in Section . Assuming a functional form allows me to compute the capitalization effect for any combination of these two variables. Third, I compare the capitalization in the alternative scenario to the baseline and report the change for the median affected property in Tables 4 and 5. Fourth, I add up capitalization effects translated to dollars-as described at the end of Section 4- and reported the accumulated change.