

Take the Q train: Value capture of public infrastructure projects[☆]

Arpit Gupta^a, Stijn Van Nieuwerburgh^{b,c,d,*}, Constantine Kontokosta^e



^a Department of Finance, Stern School of Business, New York University, 44 W. 4th St, New York, NY 10027, United States

^b Department of Finance, Graduate School of Business, Columbia University, Uris Hall 809, 3022 Broadway, New York, NY 10027, United States

^c NBER

^d CEPR

^e Marron Institute for Urban Management, New York University, 60 5th Ave, 2nd Floor, New York, NY 10011, United States

ARTICLE INFO

JEL classification:

G10
G50
R32
R41
R42
R51

Keywords:

Infrastructure finance
Real estate
House prices
Public finance
Urban transit
Value capture
Commuting

ABSTRACT

Transit infrastructure is a critical asset for economic activity yet costly to build in dense urban environments. We measure the benefit of the Second Avenue Subway extension in New York City, the most expensive urban transit infrastructure project in recent memory, by analyzing local real estate prices which capitalize the benefits of transit spillovers. We find 8% price increases, creating \$5.5 billion in new property value. Using cell phone ping data, we document substantial reductions in commuting time especially among subway users, offering a plausible mechanism for the price gains. The increase in prices reflects both higher rents and lower risk. Infrastructure improvements lower the riskiness of real estate investments. Only 30% of the private value created by the subway is captured through higher property tax revenue, and is insufficient to cover the cost of the subway. Targeted property tax increases may help governments capture more of the value created, and serve as a useful funding tool.

1. Introduction

Transit infrastructure is an essential urban asset, but can be expensive to construct. Local governments must be able to identify the benefits of infrastructure investments and isolate revenue streams to finance such costly but important projects. To do so, many urban governments practice land value capture—supplying public transportation by taxing property owners. If public transit benefits are capitalized into property prices, then municipalities can potentially fund essential infrastructure projects by levying higher property taxes. However, measuring the benefits of transit projects (both monetary and non-monetary), and hence the scope for value capture taxes, remains an important challenge.

Our paper uses the Second Avenue subway extension in New York City—the most substantial subway expansion in recent decades—to estimate the impact of such investments on commuting time, prices, and rents. These inputs are essential to estimate the possibility of value cap-

ture: how much windfall gain from infrastructure projects could be potentially recouped to cover the cost of investment through tax instruments. Prior literature has identified several potential benefits of subway construction projects—improved access to workplaces and amenities due to shorter commuting times (Kahn and Baum-Snow, 2000; 2005; Severen, 2018), lower traffic congestion on roads and other public transportation, and reduced pollution (Anderson, 2014).¹ These diffuse benefits are often difficult to measure directly, complicating a straightforward cost-benefit calculation. Failure to appropriately account for private-sector benefits may result in important infrastructure investments remaining unfunded.

¹ Other associated benefits of new transit linkages include improved urban amenities such as increased retail presence (Kahn, 2007), noise and crime re-

* We gratefully acknowledge financial support from the Lincoln Institute and the NYU Stern Infrastructure Initiative, as well as comments from conference participants at the CREFR Spring Conference, the PREA Institute Conference in NYC, the AREUEA National Conference 2020, the Stanford Hoover Institute infrastructure conference, the 2019 Urban Economics Association conference, the Virtual Real Estate Seminar, CUNY Baruch, and NBER Summer Institute (Real Estate/Urban). We thank Yuan Lai, Michael Leahy, and Joshua Coven for superb research assistance.

^{*} Corresponding author.

E-mail addresses: arpit.gupta@stern.nyu.edu (A. Gupta), svnieuwe@gsb.columbia.edu (S. Van Nieuwerburgh), ck2218@nyu.edu (C. Kontokosta).

We address the challenge of measuring benefits from transit expansion by tying the improvements in commuting time to appreciation in real estate, which capitalizes the present value of all future benefits that accrue to households and businesses from these transportation gains. We find large effects of the transportation investments—real estate values rose by 6–10% in the vicinity of the subway stop, relative to other properties in the surrounding neighborhood of the Upper East Side. These estimates are high enough that they would pay for the subway by itself, suggesting that this project passes a cost-benefit test despite the high construction expenses. However, despite the value generated from the project, the bulk of these gains were captured by private investors and did not accrue to the government. As the Henry George theorem would suggest (Stiglitz, 1977), local governments should tax the incremental property value gain which results from public goods investment. Taxing this surplus windfall that accrues to local landowners would leave landowners no worse off than they were before, while providing essential funding to finance essential projects.

Our analysis makes progress on the measurement of the benefits of infrastructure improvements in two ways. First, we provide novel estimates on the commuting time benefits of subway construction using granular location data. Second, we then take advantage of the fact that transportation infrastructure and real estate assets are complements; as a result, real estate values in the vicinity of public transportation hubs capitalize the present value of all future benefits that accrue to households and business from transportation gains. To perform this calculation, we measure how residential and commercial real estate asset values change after the extension of public transportation using granular property transactions data.

We estimate the gains in commuting time and real estate prices through a difference-in-differences approach. We define geographical areas that are “treated” by the subway extension. We compare the changes in real estate values in the treated areas to the changes in real estate prices in the “control” areas in a difference-in-differences setup. Our baseline treatment definition selects all properties in a rectangular area between 59th and 100th streets and between First and Third Avenues (the “2nd Avenue corridor”). The control area is the rest of the Upper East Side (UES) of Manhattan, the remaining properties between 59th and 100th streets between Fifth Avenue and the East River. We consider three alternative treatment definitions. The second treatment is defined as the area within a 0.3 mile walking distance from one of the three new stations that were added as part of the subway expansion. The third treatment definition considers buildings whose distances to the nearest station on any subway line are reduced after the opening of the new subway stations. The fourth treatment looks at the intersection of the first three treatment definitions.

The Q-line extension opened on January 1st 2017. We start the Post period four years earlier, to capture the fact that there was little residual uncertainty over eventual subway completion as early as 2013. Since real estate prices are forward-looking, they should anticipate the benefits from the future subway extension. In a second specification, we break up the pre-2013 period into the pre-2006 and the 2007–2013 periods. This specification allows for six additional years of potential anticipation effects. It also captures potential disamenities (noise, pollution, business disruption) from heavy construction, which was concentrated in 2007–2013.

Our data combines deeds and property tax records from NYC's Department of Finance with unit and building characteristics scraped from StreetEasy, an online real estate listing platform. Our final sample covers about 50,000 arms length transactions of condo and coop units on the UES. From the same data source, we also collect rental listing information on about 100,000 rental units. We augment this sample with high-frequency geolocation information from mobile phones, which al-

lows us to track exact commute lengths at the individual level, before and after the subway opening, as well as the mode of commuting.

We find compelling evidence that the 2nd Avenue Subway expansion led to strong changes in commuting patterns. Using our benchmark difference-in-differences specification, we find that residents in areas served by the new subway expansion experience a decline in commute lengths of 3–5 minutes (7.5% reduction). These gains increase to 14 minutes among subway commuters. We find evidence that new migrants into the area, who are likely to be marginal price setters in the real estate market, are disproportionately likely to take the Q-train.

We then link the subway expansion to a sizable increase in real estate values. Our benchmark difference-in-differences specification estimates a 8% increase in real estate values when comparing the prices ten years before 2013 to the prices six years after. Prices on the 2nd Avenue corridor increase 10.8% relative to 2003–2006, with nearly half of this gain (5.0%) manifesting during the construction period 2007–2013. The three alternative treatment definitions result in similar point estimates: 5.6%, 5.5%, and 6.6% when comparing the post-period to the entire pre-period, and 8.5%, 7.2%, 7.6% when comparing the post-period to the pre-2006 period.

We also estimate specifications which control more finely for building amenity effects through the use of building fixed effects or unit-specific characteristics through a repeat-sales approach. Though smaller, the 2–6% price increases we find in these specifications still suggest substantial value creation in the area around subway construction.

We find evidence that larger and newer housing units experience a larger value gain. We conjecture that one channel through which the subway created increases in real estate values was the stimulus of real estate development. Certificate of occupancy data confirm a positive housing supply response that is (at least directionally) consistent with this channel.

Using the same difference-in-differences model as for sales, we show that rents also increase significantly in response to subway construction. The timing of the rent increases helps establish the presence of disamenity effects during the heavy construction phase. Combining the treatment effects of prices and rents, we find a significant increase in the price-rent ratio. According to the present-value model of Campbell and Shiller (1988), this likely reflects both expectations of higher future rent growth and lower future returns (risk premia). Indeed, Campbell et al. (2006) and Plazzi et al. (2010) show that discount rate variation is an important driver of price-rent ratio variation in U.S. real estate. Infrastructure improvements lower the riskiness of real estate investments. While intuitive, this is a novel benefit of infrastructure investment not considered hitherto in the literature.

One potential source of lower risk premia is that the subway changes the marginal agent in housing market. While the data is sparse, we find some evidence of rising incomes for new residents to the treatment area. Such gentrification could change the volatility of consumption growth of the marginal home buyer or the correlation of her consumption growth with house price growth.

In the last part of the paper, we estimate the aggregate real estate value created by the subway extension, and how much of that value flows back to government coffers in the form of higher property taxes. This analysis proceeds in several steps. The first step is to value the stocks of owner-occupied residential, renter-occupied residential, and commercial real estate in the treatment area prior to the subway (as of 2012). To that end, we combine our main data set on residential units that are sold or rented in our sample period and on the total number of units in the building with a data set on property tax assessments, and with our dynamic DiD estimation. Our approach estimates a \$31 billion aggregate valuation for owner-occupied residential, \$26 billion for renter-occupied residential, and \$12 billion for commercial real estate properties on the 2nd Avenue corridor in 2012. Second, we apply our baseline 8% price increase estimate to the \$69 billion in aggregate property value, resulting in a \$5.53 billion windfall to private real estate

ductions around stations (Bowes and Ihlanfeldt, 2001), higher labor force participation (Black et al., 2014), and less drunk driving (Jackson and Owens, 2011).

owners. Third, we analyze how much of this value creation flows back to the government. To the extent that the property tax system is able to recoup some of these expenses, this provides a natural mechanism for local governments to finance infrastructure investments. However, there are good reasons to think that the local government captures only part of the value created. Detailed analysis of property tax data shows that NYC recuperates 30.6% of the increase in market values in present value terms. This amounts to \$1.69 billion in extra property tax revenue. As a result, though the subway generated more value than the \$4.5 billion cost of construction, this value largely accrues to private landowners, rather than the city government.

This analysis motivates the possibility for additional value capture taxes which may help recoup an additional component of the investment cost, and thereby make possible additional public infrastructure investments. Cities like Tokyo and Hong Kong have successfully employed such value capture in the past. Our findings are policy-relevant and timely given ongoing debates in New York City on the future extension of the 2nd Avenue Subway line, the repair of the L line, and the East Side access project. They also have ramifications for the broader debate on how to finance an upgrade to U.S. infrastructure assets and how to provide new infrastructure in developing countries whose governments have limited borrowing and taxation capacities. Given that infrastructure projects entail enormous expenditures of public resources, it is essential to have a full accounting of the total benefits resulting from these infrastructure expansions, which our work helps to provide.

Literature Review

Our paper relates to a large literature investigating the effectiveness of infrastructure investments. Previous research has found a wide range of estimates for the return on infrastructure investment, depending on the assumptions made on the efficiency of an expansion of the public capital stock, the strength of the crowd-out effect on private investment, and the timing vis-à-vis the business cycle (Cadot et al., 2006; Andonov et al., 2019; Castells and Solé-Ollé, 2005; Finkenzeller et al., 2010; Bom and Lighthart, 2014; Ramey, 2020). The uncertainty over these estimates suggests that the approach of inferring the returns to infrastructure investment from real estate return is a useful complement to the traditional approach.

Our paper also belongs to an active literature that studies the land or house price capitalization of urban rail.² Price premium estimates for real estate surrounding transit hubs typically range from 3% to 10%, with some outliers at the upper end of 40–45%. Kahn (2007) finds that new public transit has the biggest impact on real estate prices when the new transit connects an area to a vibrant downtown, which is the case for the New York City 2nd Avenue subway expansion. A few studies have identified negative relationships between distance to transit stations and prices (Bowes and Ihlanfeldt, 2001; Pan and Zhang, 2008), reflective of disamenities of transit stations (e.g. crowding, noise, and crime). Our paper is the first to study the recent subway expansion in New York City. The New York City subway system is one of the oldest and most widely used public transit systems, and the one with the most stations. As argued, this expansion was the most expensive per-mile expansion in U.S. transportation history. The urban density and pre-existing transportation network make for an important and interesting context.

We contribute further by investigating the interplay between the ownership market (condos and coops) and the rental market. Our results indicate that infrastructure improvements affect both the cash flows

² See Dewees (1976) for Toronto, McDonald and Osuji (1995); McMillen and McDonald (2004); Diao et al. (2017) for Chicago, Cervero and Duncan (2002) for San Jose, Lin and Hwang (2004) for Taipei, Hess and Almeida (2007) for Buffalo, sixteen cities among which Atlanta, Boston, Chicago, Portland, and Washington DC by Kahn and Baum-Snow (2005), Zheng and Kahn (2013) for Beijing, Fesselmeyer and Liu (2018) for Singapore, and Zhou et al. (2020) for Shanghai. Also see the structural analysis of transit improvements in Heblitch et al. (2020) for historic London and Ahlfeldt et al. (2015) for post-reunification Berlin.

and their riskiness, allowing us to connect to the asset pricing literature on the role of cash flows and discount rates in the stock market (Campbell and Shiller, 1988; Kojen and Van Nieuwerburgh, 2011; Cochrane, 2011) and in real estate markets (Campbell et al., 2009; Plazzi et al., 2010; Van Nieuwerburgh, 2019). We find that infrastructure investments increase cash flows and lower the risk of real estate investments.

A new literature, including Athey et al. (2019), Chen et al. (2019), and Chen and Rohla (2018), has begun to use rich geolocation data from smart phone pings to track individual trajectories. Our paper is the first to use this data to study commuting lengths. This data is uniquely well-suited to this task because ping data allow us to capture actual commuting lengths, rather than the estimated commuting lengths from surveys used in prior research (as in Couture et al. (2018)). Doing so allows us to quantify the transportation gains resulting from the subway extension, which we then tie to complementary real estate valuation gains.

The rest of the paper is organized as follows. Section 2 provides institutional background. Section 3 contains the empirical specification. Section 4 discusses the data. Section 5 analyzes our commuting results. The main real estate valuation results are in Section 6. Section 7 contains the analysis on rents and price-rent ratios. Section 8 computes the aggregate value creation from the subway extension and how much of it flows back to the government. Section 9 concludes. The Appendix contains additional empirical results and sensitivity analysis.

2. Institutional background

Elevated rail lines were formerly running on 2nd and 3rd Avenues in New York as a part of citywide system of “el” trains operated by privately managed and jointly funded companies. This network was gradually replaced with underground subways starting in 1904. A Second Avenue Subway, in particular, was a major component of a subway expansion proposed in 1920 by the Independent Subway System (IND), a publicly owned and operated managed entity. Ultimately, the IND was combined with two other private companies and placed under government control. The elevated 2nd Avenue line was torn down in 1942 in anticipation of a new underground 2nd Avenue Subway. However, construction plans hit numerous difficulties across several decades, including the Great Depression, World War II, and the NYC funding crisis of the 1970s, and remained a “pipe dream.”

The Metropolitan Transportation Authority started a new study exploring various options for the 2nd Avenue subway in 1997 and approved an environmental impact statement in 2004. New York voters passed a crucial transportation bond issue to fund the expansion in November 2005. The Department of Transportation authorized funding for construction in 2006. Construction work on the line started in 2007. Construction of the subway tunnel was completed in 2011. By 2013, it was clear that the end of construction was on the horizon and a Community Information Center opened up on the UES. The grand opening of the subway was on January 1, 2017. Fig. 1 shows the timeline.

Figure 2 highlights the subway line in the context of the local area. The Q-line runs for 8.5 miles, including the 1.8 mile stretch of the completed 2nd Avenue Subway extension between 59th Street and 96th Street. The construction included three new subway stations on 2nd Avenue at 72nd Street, 86th Street, and 96th Street, as well as a subway tunnel connection to the existing Q-line stop on 59th Street and Lexington Avenue.

This extension connected the eastern portion of the Upper East side of Manhattan to the rest of the subway grid of New York City, adding a spoke to the network. Since the eastern part of the UES is mostly a residential area, it attracts few in-bound commuters nor does it have much in the way of urban amenities. For these reasons, the general equilibrium effects on commuting times and property values outside the UES are likely to be small.

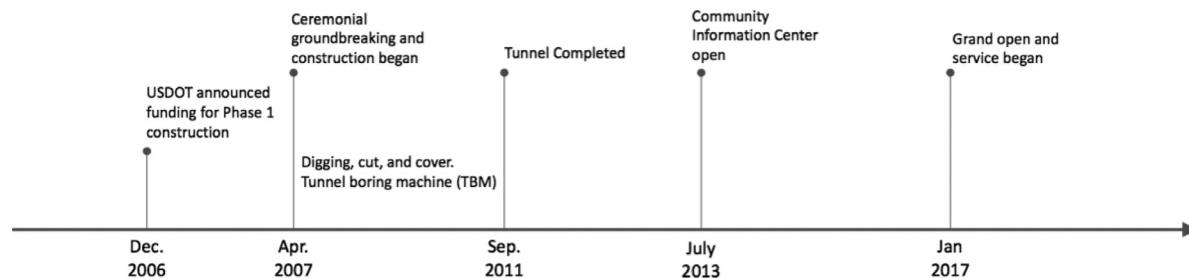


Fig. 1. Timeline of construction.



Fig. 2. Subway map on the upper east side of Manhattan.

The total cost of the 2 mile expansion project was \$4.5 billion, making the expansion the most expensive subway construction project per mile in history.³ In terms of funding sources, \$1.3 billion in funding to support the program was provided by the Department of Transportation, \$690 million was provided by the MTA, and \$2.9 billion was supplied by the State of New York (as a bond approved by ballot measure). Our value capture analysis abstracts from the specific funding provided by different agencies. We assume that all construction costs and benefits are borne by one consolidated governmental agency capable of levying property taxes.

3. Empirical specification

3.1. Baseline definition of treatment areas

The key empirical challenge is that the value of real estate depends on a myriad of factors beyond the opening of a new subway line. Other changes in the local economic environment may confound the effects

from the transit improvements on real estate values. As a consequence, estimating the causal effect of the subway construction on prices and rents poses several economic challenges. We first describe several of these pitfalls, and then describe how our empirical approach addresses the challenges.

We need to construct treatment boundaries to define the areas affected by subway expansion, compared to control areas which are less affected by the subway construction itself. Defining the appropriate cross-sectional treatment areas is important to ensure that we estimate the appropriate spillover benefits of the infrastructure project. Additionally, we need to define the right time periods affected by the subway construction. This entails considering both possible anticipation effects (price increases that materialize in anticipation of subway construction), as well as disamenities associated with subway construction. Finally, we need to consider carefully how greater housing demand may impact the local market. New residents impact, potentially differentially, both the rental and housing market; with implications for both prices and quantities. Additionally, the sorting of new residents may displace some current residents.

To address these challenges, we carefully construct a difference-in-differences approach. We first define treatment areas to capture the regions most affected by the subway construction, and validate these choices based on realized commuting decisions. We also consider a dy-

³ An interesting question, outside the scope of this article, is why construction was so expensive. An investigation by the New York Times explores several possibilities. See <https://www.nytimes.com/2017/12/28/nyregion/new-york-subway-construction-costs.html>.

namic difference-in-differences specification, which allows for variation in timing effects. Finally, we consider a range of outcomes—including both prices and rents—and assess the implications of our results for discount rates.

Our baseline specification defines a treatment group which is most affected by subway construction, in contrast to a control group representing less strongly affected properties in the neighboring region. We define the treatment group to be all the land parcels between 59th street and 100th street and between First Avenue and Third Avenue, taking the midpoint of the avenues as the demarcation line. This is what we call the 2nd Avenue corridor. Our control group consists of three corridors that make up the rest of the UES. The Lexington Avenue corridor is the collection of parcels between 59th street and 100th street and between Third and Park Avenues. The Madison Avenue corridor is the collection of parcels between 59th street and 100th street and between Park and Fifth Avenues. Its western border is Central Park. Finally, the York Avenue corridor is the collection of parcels between 59th street and 100th street to the east of the midpoint of First Avenue. Its eastern border is the East River.

This choice of baseline treatment and control group is driven by a trade-off between minimizing the treatment effect on the control group and maximizing the similarity in terms of common drivers of real estate valuations. By differencing out trends in real estate values in the control group, we remove common drivers of real estate prices that affect the entire area (UES) and isolate the effects of the subway extension. The difference-in-differences framework is appropriate in our context because the subway construction led to only minor effects on the entire system beyond those that accrued to the treatment area. The standard concern of aggregate benefits due to network effects is severely mitigated because the expansion arose in the outer edge of the network and in a residential area.

The Lexington Avenue corridor is geographically the closest to the 2nd Avenue and may be affected the strongest by the neighborhood trends that affect real estate valuation on 2nd Avenue other than the subway extension. However, Lexington Avenue may also be directly affected by the subway extension. Residents in the Lexington corridor benefit from the new subway line, either because it directly shortens their commutes or because it alleviates congestion on Manhattan's busiest line, the 4-5-6, which runs under Lexington Avenue and parallel to the Q-line. The resulting improvement in transportation from the 2nd Avenue subway extension may affect real estate values in the Lexington Avenue corridor. Removing those effects tends to bias downward our estimate of the value created by the subway extension. A countervailing effect that tends to bias our treatment effects estimation upward is that the subway expansion may have made 2nd Avenue more competitive in terms of attracting residential, retail, and other commercial tenants away from Lexington Avenue.

Residents living in the York Avenue corridor also potentially benefit from the Q-line extension. Indeed, for most of them, the new 2nd Avenue subway stations are the closest ones. We consider York Avenue corridor residents to be in the control group in our baseline specification because they are fairly far from the new subway stations. However, we study alternative treatment definitions in [Section 6.5](#) where properties in the York Avenue corridor are part of the treatment group.

We further examine local spillover effects in our analysis in [Section 6.4](#) in which Madison Avenue is the control group, and confirm a null effect for price effects on Lexington Avenue and weak positive effects for York Avenue. This further justifies our choice of putting Lexington Avenue in the control group, and limiting our spatial analysis to the neighborhoods around the subway construction.

Panel A of [Fig. 3](#) indicates the buildings where we have at least one apartment transaction in our sample. Apartments in treated buildings are colored in blue while buildings in the control sample are in red. The large black dots indicate subway stations on the UES, including the three new stops on the 2nd Avenue subway.

A second research design question is where to draw the demarcation line between the pre- and post-treatment periods. The subway went into operation on January 1st, 2017. While there was considerable uncertainty about the exact opening date until the last minute, eventual project completion was long anticipated. Construction started in April 2007. Tunnel excavation began in May 2010 and blasting concluded in March 2013. In 2011, the original 2013 completion date was pushed back to December 2016. This project design presents two possible threats to identification: the possibility of anticipation effects as well as construction disamenities. These represent significant challenges to identification, which we address through construction of appropriate treatment windows.

Anticipation effects are important in our context because forward-looking developers and property owners willing to tolerate the inconvenience of the construction project could capture some of the potential future benefits by acting prior to the subway opening. These anticipatory effects should be reflected in real estate prices, which reflect the expected discounted value of future rents. In our benchmark analysis, we strike a middle ground and take January 1st 2013 as the demarcation line between the before and after. This allows for four years of anticipation effects prior to the inauguration of the new subway line. A subway community information center was opened in 2013, signaling that project completion was no longer in doubt. This choice also provides a large enough sample in the before and after period.

We accommodate additional possible anticipation effects by allowing for a separate construction period control from 2007–2012. Under these specifications, we only compare price trends after 2013 with those before funding for the program was announced. Anticipation effects are likely to be minimal under this approach. Additionally, the construction period allows for differential disamenity effects, associated with nuisances related to the construction itself. The interpretation of price effects during the construction period, as a result, is complicated due to the presence of both anticipation and disamenity effects. However, the interpretation of our post-treatment period is relatively clean in that it is designed to capture neither anticipation nor construction effects. We also estimate effects dynamically year-by-year, which allows for more fine-grained analysis of time trends. A comparison of dynamic treatment effects for prices and rents allows for a better separation of disamenity and anticipation effects.

3.2. Empirical specification

Our core empirical specifications are difference-in-differences specifications defined across two dependent variables: commute times and real estate transaction prices. While transit expansions may have complicated impacts on real estate prices throughout the entire transportation network, several aspects of our research setting argue for a more local approach. First, the 2nd Ave expansion did not cut across several pre-existing lines, but instead jutted out as an additional spoke into a previously unserved neighborhood. Second, the region of the UES that was affected by the construction does not have a substantial office presence nor major urban amenities that attract visitors. Instead, the area is predominantly residential, and locals are able to use the subway to commute to work through a faster route. These distinctive features of the subway construction justify a difference-in-differences specification. While we expect general equilibrium effects on prices resulting from a more complete infrastructure system to be small in our setting, such effects would bias down our estimates, making our conclusions on value creation conservative.

Our baseline regressions can be expressed as:

$$y_{it} = \alpha + \gamma_1 \cdot \text{Treatment}_i + \delta_1 \cdot \text{Post}_t + \beta_1 \cdot \text{Treatment}_i \times \text{Post}_t + X'_{it} \cdot \theta + \epsilon_{it}, \quad (1)$$

For our commuting regressions, y_{it} represents commute time for a person i in seconds. The omitted pre-period in this analysis refers to the period



Fig. 3. Treatment based on distance to new stations. Notes: Panel A shows treatment definition 1 which corresponds to properties that are on the 2nd Avenue Corridor defined as between 1st and 3rd Avenues. Panel B shows treatment 2 which consists of properties that are within 0.3 miles in walking distance of one of the new Second Avenue stops. Panel C shows treatment 3 which captures properties with a reduction in distance to the nearest subway station. Panel D shows treatment 4 which is the intersection of the first three treatments.

June 2016–December 2016; and the “Post” period refers to the time after subway construction, from January 2017–August 2017. The resulting β_1 coefficient captures the impact of subway construction on commuting times.

For our real estate pricing regressions, y_{it} reflects the log transaction sale price of a unit i in period t . We consider a much longer time span in our real estate analysis, with the pre-period making up January 2003–December 2012; and our post-period January 2013–March 2019. The key parameter of interest is β_1 , which corresponds to the treatment effect corresponding to our various treatment definitions (for instance, properties along the 2nd Avenue corridor), in the period.

We also estimate a triple-interaction specification with an indicator for subway usage:

$$\begin{aligned} y_{it} = & \alpha + \gamma_1 \cdot \text{Treatment}_i + \delta_1 \cdot \text{Post}_t + \beta_1 \cdot \text{Treatment}_i \times \text{Post}_t + \mathbf{X}'_{it} \cdot \theta \\ & + \delta_2 \cdot \text{Subway}_{it} + \beta_2 \cdot \text{Subway}_{it} \times \text{Post}_t \\ & + \delta_3 \cdot \text{Subway}_{it} \times \text{Post}_t \times \text{Treatment}_i + \varepsilon_{it}. \end{aligned} \quad (2)$$

In this specification, a key coefficient is δ_3 , which captures the differential effect of being in the treatment area, in the post period, for subway users.

To investigate the presence of additional anticipation effects, we also consider an empirical specification using our real estate outcomes which splits the “Pre” period into two subperiods: January 2003–December 2006 and January 2007–December 2012. We call the latter period the Construction Period because it coincides with the period of heavy tunnel blasting. In those specifications, real estate prices in the Construction and Post periods are estimated relative to the omitted 2003–06 period. This specification is:

$$\begin{aligned} \ln(p_{it}) = & \alpha + \gamma_1 \cdot \text{Treatment}_i + \delta_1 \cdot \text{Post}_t + \beta_1 \cdot \text{Treatment}_i \times \text{Post}_t + \mathbf{X}'_{it} \cdot \theta \\ & + \delta_2 \cdot \text{Construction Period}_t \\ & + \beta_2 \cdot \text{Treatment}_i \times \text{Construction Period}_t + \varepsilon_{it}. \end{aligned} \quad (3)$$

The additional parameter of interest is β_2 , which corresponds to the relative price increase in the construction period (2007–12) relative to the earlier period (2003–06). The coefficient is the net effect of early antic-

ipatory price effects and disamenity effects resulting from the construction.

Our difference-in-differences analysis accounts for the level differences in prices between treatment and control areas. However, if there are changes over time in the average characteristics of transacted properties which differ between treatment and control group, then that could affect the estimate of the subway extension. Therefore, our main specifications will control for building and housing unit characteristics X_{it} . We also consider a specification that adds building fixed effects. We account for the spatial autocorrelation of errors by clustering standard errors at the Census Block level, and also consider a robustness specification (Appendix Table A1) with two-way clustering along Census Block and year, finding similar effects.

We focus on whether we observe convergence in prices. If the value gap for the 2nd Avenue corridor is driven by scarce access to public transportation options, we expect price convergence after subway construction.

To directly test for the presence of confounding variables, we also examine changes in median income along the 2nd Ave corridor as well as other parts of the UES in Appendix A.1. We find that both treatment and control areas appear to be along parallel trends in terms of income growth well prior to the subway's construction, going back to 1990, and showing little differential change through subway construction. These factors argue against the idea that the subway's construction was motivated by differential trends in the area, or that exposure to concurrent confounding factors such as gentrification may be otherwise biasing our results. This is consistent with Nobbe and Berechman (2013), who argue that the 2nd Avenue subway project selection and completion was largely determined by local politics rather than transport-economic considerations.

4. Data

4.1. Location data

Mobile location data was obtained from VenPath—a global provider of compliant smartphone data. Our data provider aggregates information from approximately 120 million smart phone users across the United States. Global Positioning System (GPS) data were combined across applications for a given user to produce pings corresponding to time stamp-location pairs. Ping data include both background pings (location data provided while the application is running in the background) and foreground pings (activated while users are actively using the application). Ping data provides nearly continuous-time location information (every 1–3 seconds) throughout the day. Our sample period covers June 2016–October 2017, an ideal time frame since the subway opened on January 1st, 2017, right in the middle of this time frame.

To identify commuting lengths, we use the panel dimension of our mobile phone data. We use a Microsoft open-source data set to define the physical footprint of buildings.⁴ We isolate possible home locations by first selecting all nighttime pings by a building's users (from midnight to 7am). We require that users have a minimum presence in the buildings of three night-time pings on five different days. Then, to identify homes for these users, we require that these users ping at possible home locations at least twice on two different nights. We then pick the home location as the building in which individuals ping most often over the sample. Similarly, we define possible work locations as the building in which individuals ping most often between the hours of 10am–1pm and 2pm–7pm. We select the building with the most frequent day-time ping activity as the work location. This classification produces a list of home and work locations, from which we select those with home locations on the UES.

⁴ See <https://github.com/microsoft/USBuildingFootprints>.

We define morning commute length as the time difference between the last ping observed in the home location, and the first ping observed in the work location. Evening commutes are similarly defined as the difference in time between the last ping observed at work and the first ping observed at home. We require that commutes be at least 0.4 km in distance, and so exclude individuals who work at home or have minimal commutes. Commutes are expressed in seconds. The final sample contains 27,549 commutes.

We define a subway commuter as an individual who pings close to a subway stop on either the Q line or the 4-5-6, and one other station in NYC during the commute time window. We define a recent mover as a user whose home location is in the UES after January 1, 2017 and elsewhere before.

To validate our sample coverage against the general population, we find a 78% correlation between population counts at the ZIP-level between our sample population and the Census-reported population. Looking across demographic categories, we find little relationship between racial composition and age against the fraction of devices present within each ZIP code. We find more modest correlations (0.196) of the fraction of devices present against the fraction of locals with Bachelor's degrees. We conclude that our mobile phone data appear broadly representative of the population, and in particular appear balanced on age and racial composition; while they may skew slightly towards the more educated. Appendix A.2 provides the details.

4.2. Condo and coop sales data

We build a new dataset of all residential transactions on New York City's UES from January 2003 until March 2019. The two primary data sources are the New York City deeds records and StreetEasy.

The deeds records have information on the sale price, sale date, address, as well as a tax ID (the BBL code). From StreetEasy we collect information on all past residential real estate sales on the UES via web scraping. We add properties between 96th Street and 100th Street, which StreetEasy considers to be part of East Harlem. We also eliminate properties that are above 100th Street along Fifth Avenue, which StreetEasy considers to be part of the UES.

StreetEasy has apartment unit and building characteristics, which are absent in the deeds records. We obtain the following building characteristics: exact street address, latitude and longitude, year of construction of the building, and building amenities. The amenity vector contains: doorman, bike room, gym, elevator, laundry room, concierge, live-in super, pool, storage room, roof deck, children's playroom, parking. Based on the exact location, we use Google Map's API to compute walking distance to Central Park, a major amenity, and walking distance to Grand Central Terminal, a major employment center.

The unit characteristics we have are apartment unit name (e.g. 17A), the number of bedrooms, number of bathrooms, an indicator variable for condo, an indicator variable for coop, an indicator variable for studio, the square footage of the unit, and of course the transaction date and the transaction price. We infer the floor of the unit based on the apartment unit name.

A text field in the StreetEasy data describes the transaction in more detail. Based on the text field, we eliminate transactions that are commercial space, storage units, maid's rooms, parking spots, or garages. We also eliminate units that have zero bathrooms and zero bedrooms but are not studios. Importantly, we remove all "sales" which are neither reported as "sold" nor as "recorded closing." Cross-checking against the deed records database reveals that these "sales" are not actual sales but merely removed listings.

We express all transaction prices in real terms by scaling by the Consumer Price Index based in December 2017. We then eliminate all transactions with a real price below \$400,000 and above \$10 million. Transactions below \$400,000 in 2017 dollars are unlikely to be arms-length transactions for actual apartment units on the Upper East Side of Manhattan. Transactions above \$10 million are unlikely to be affected by

Table 1
Summary statistics.

Panel A: Treatment Group								
	N	Mean	St.Dev	p1	p25	p50	p75	p99
Sale Price	17,161	\$1,216,759	\$1,047,535	\$408,451	\$611,908	\$845,036	\$1,405,996	\$5,801,661
Sq. Ft.	11,906	1093	670	423	710	905	1300	3200
Price Per Sq. Ft.	11,888	\$1120	\$431	\$422	\$837	\$1030	\$1327	\$2477
bedrooms	17,143	1.617	0.954	0	1	1.205	2	4
bathrooms	16,771	1.565	0.860	1	1	1	2	5
condo	17,161	0.411	0.492	0	0	0	1	1
coop	17,161	0.589	0.492	0	0	1	1	1
studio	17,161	0.056	0.230	0	0	0	0	1
building age	17,161	43.283	23.199	1	28	43	55	98
vintage2	17,161	0.068	0.252	0	0	0	0	1
closest pre	17,161	0.323	0.116	0.057	0.245	0.313	0.395	0.551
closest post	17,161	0.183	0.085	0.007	0.111	0.186	0.247	0.364
dist change	17,161	0.139	0.129	0	0.014	0.109	0.241	0.429
Treatment 2	17,161	0.806	0.396	0	1	1	1	1
Treatment 3	17,161	0.789	0.408	0	1	1	1	1
Treatment 4	17,161	0.727	0.445	0	0	1	1	1

Panel B: Control Group								
	N	Mean	St.Dev	p1	p25	p50	p75	p99
Sale Price	27,138	\$1,986,550	\$1,804,922	\$415,858	\$760,199	\$1,324,442	\$2,492,960	\$8,839,228
Sq. Ft.	14,427	1322	859	420	774	1100	1600	4005
Price Per Sq. Ft.	14,368	\$1289	\$608	\$459	\$883	\$1145	\$1514	\$3420
bedrooms	27,091	1.969	1.039	0	1	2	2.812	5
bathrooms	26,445	1.896	1.041	1	1	2	2.5	5
condo	27,138	0.323	0.468	0	0	0	1	1
coop	27,138	0.677	0.468	0	0	1	1	1
studio	27,138	0.031	0.173	0	0	0	0	1
building age	27,138	57.81	27.883	1	40	55	82	108
vintage2	27,138	0.044	0.206	0	0	0	0	1
closest pre	27,138	0.332	0.219	0.022	0.16	0.271	0.481	0.851
closest post	27,138	0.259	0.139	0.022	0.153	0.237	0.348	0.594
dist change	27,138	0.073	0.125	0	0	0	0.095	0.429
Treatment 2	27,138	0.216	0.411	0	0	0	0	1
Treatment 3	27,138	0.320	0.466	0	0	0	1	1
Treatment 4	27,138	0	0	0	0	0	0	0

the 2nd Avenue subway and distort sample averages. The final sample contains 44,299 transactions.

Table 1 provides summary statistics from our data. The top panel reports properties on the 2nd Avenue Corridor, which are treated according to our baseline treatment area definition. The bottom panel reports properties in the baseline control group (Madison Ave, Lexington Ave, and York Ave corridors). We have 17,161 sales in the treatment group and 27,138 in the control group, so that 38.7% of transactions are treated observations. The average property on 2nd Avenue costs \$1.22 million, is about 1093 square feet large, costs \$1119 per sqft, has 1.6 bedrooms bathrooms, and is in a building that is 43 years old at the time of transaction. The treatment group has 40% condos and 60% coops. Apartments in the control group cost substantially more. The typical sale price is \$1.99 million or \$1289 per sqft. Units are 200 sqft larger, have 2 bedrooms and 1.9 bathrooms, and are older (58 years). There is a smaller fraction of studios (3% vs. 6%), while the condo-coop breakdown tilts more towards coops at 30%–70%.

4.3. Rental data

We also collect data from StreetEasy on all rental buildings in the UES. For each apartment unit in the rental data (with a rental listing at some point between 2006 and 2019) we obtain the same unit and building characteristics as for the sales transactions sample: exact location (in treatment area or not, distance from Central Park, distance from Grand Central), number of bedrooms, number of bathrooms, studio flag, floor, the same building amenities as listed above, year built, and total number of units in the building.

5. Commuting length results

We begin with an analysis of how the extension of the 2nd Avenue Subway affected commute lengths. **Table 2** shows the results from the difference-in-differences estimation of [equation \(1\)](#) with commute length (expressed in seconds) as the dependent variable. The Post period refers to January–October 2017, the period after subway opening. We use four treatment definitions corresponding to the benchmark Second Avenue corridor treatment, defined above, and three alternative definitions of treatment, defined in more detail in [Section 6.5](#).

Panel A of this table shows the effect of subway extension on commute times for all affected residents, regardless of their choice of commuting method. Our baseline specification, in column 1, shows a reduction in typical commute lengths of 193 seconds (over 3 minutes) for smart phone users who live in the treated corridor. This is a 7.4% reduction relative to a pre-treatment mean commuting time of 43.6 minutes in the treatment group. We find comparable treatment effects between 160 and 251 seconds when looking at alternate treatment definitions in the remaining columns. The effects are estimated precisely. Before the Q-line extension, residents in the Second Ave corridor commute 359 seconds (6 minutes) longer than other residents in the UES. The new subway line closes the average commuting gap by more than half, effectuating substantial convergence.

Panel B of **Table 2** breaks out the effect by commuting mode, as in [Eq. \(2\)](#). We are particularly interested in the triple interaction of “Subway × Post × Treatment.” Our results show that subway users experience a substantial reduction of 850 seconds (14 minutes) in commute lengths in the treated areas in the aftermath of the Q-line opening. We define subway commuters by their commute choices in the post period. As a result, our measure includes reductions in commute lengths from

Table 2
Effect of subway construction on commute times.

<i>Panel A: Treatment Corridor</i>		Commute Time (sec)			
VARIABLES		On 2nd Ave	Walking Distance	Closer Subway	Intersection
Post		-3 (35)	10 (36)	-2 (37)	8 (33)
Treatment		359*** (48)	356*** (48)	383** (47)	448*** (50)
Post x Treatment		-193*** (55)	-199*** (54)	-160*** (54)	-251*** (57)
Observations		27,549	27,549	27,549	27,549
R-squared		0.004	0.004	0.006	0.005
<i>Panel B: Interacted with Subway Use</i>		Commute Time (sec)			
VARIABLES		On 2nd Ave	Walking Distance	Closer Subway	Intersection
Post		144 (91)	149* (86)	138 (91)	175** (86)
Treatment		-324* (189)	153 (241)	99 (182)	-13 (248)
Subway		-324*** (88)	-262*** (85)	-277*** (90)	-263*** (83)
Post x Treatment		592*** (200)	631** (254)	446** (195)	563** (260)
Subway x Treatment		749*** (195)	248 (246)	330* (189)	505** (254)
Subway x Post x Treatment		-850*** (208)	-854*** (260)	-653*** (203)	-864*** (267)
Subway x Post		-182* (99)	-191** (94)	-181* (100)	-211** (93)
Observations		27,549	27,549	27,549	27,549
R-squared		0.013	0.016	0.016	0.015

Notes: Post is an indicator variable for the period from January 1st 2017–October 2017. Treatment is an indicator variable for units exposed to the subway extension that varies by column. Treatment definition 1 corresponds to properties that are on the 2nd Avenue Corridor defined as between 1st and 3rd Avenues. The second treatment definition consists of properties that are within 0.3 miles in walking distance of one of the new 2nd Avenue stops. The third treatment definition captures individuals with a reduction in distance to the nearest subway station. The fourth treatment definition is a composite requiring that all three treatments hold. Panel A runs a difference-in-differences specification, following Eq. 1, across these four treatment definitions before and after subway extension on commute times. Commutes are defined as the time difference between pings observed at home and work locations, as described in the text. Panel B shows a triple interaction with the effects broken out by whether users use the subway. Subway usage is defined as whether individuals (in the post-period) ping close to either the 4-5-6, Q-line, and one other station in NYC during the commute time window. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

individuals who shift to subway commutes from another mode of transportation in the pre-period, as well as from those who were already commuting by subway. The large improvement in commute times, concentrated among actual subway commuters in the treatment area, points to the large impact of the Second Ave subway extension on residents' access to work.

We further note that the interaction of "Subway × Post" is also significantly negative (at the 5% or 10% level depending on the treatment definition) and estimated to be around 180–210 seconds. This shows that the Q-line extension reduced commuting times also for subway users in the control area, either because they too started using the Q train to commute to work or because the Q train alleviated congestion on the 4-5-6 line.

Because our results impute subway ridership, they may be subject to some attenuation bias because we do not observe subway usage directly. We may underestimate the benefits of subway ridership as a result, to the extent that our results incorporate commuting gains by both genuine subway riders as well as other commuters in the area.

Next, we analyze the choice of commuting by splitting residents into recent movers to the UES and everyone else. Fig. 4 shows that recent movers are substantially more likely to use the Q-line as their primary

commuting choice. The difference is 16.5 percentage points, and statistically different from zero (t-stat of 2.29). Since recent movers are more likely to be the marginal buyers and renters, the large gains in commuting suggest one important channel through which the Second Avenue subway extension may have increased prices and rents in real estate markets. We investigate this in the following section.

6. Real estate capitalization results

6.1. Corridors: Baseline treatment and control

The previous section established the strong impact of the Q-line construction on commuting patterns. Individuals in treated areas saw substantial declines in commuting, driven by subway commuters. New residents were disproportionately likely to use the Q-line train. Given the complementarity between transportation improvements and real estate, we investigate the hypothesis that these transportation improvements led to valuation gains in real state markets.

Table 3 presents our main treatment estimates to measure the real estate capitalization effect of subway construction. The Post variable in this specification captures the price impact after January 2013 relative to the entire pre-period of January 2003–December 2012. In column 1,

Table 3
Main price effects - baseline treatment definition.

	(1)	(2)	(3)	(4)	(5)
Post × On 2nd Ave	0.115** (0.0430)	0.0773*** (0.0214)	0.0331** (0.0120)	0.103** (0.0335)	0.0411* (0.0185)
Post	0.0575* (0.0232)	0.0971*** (0.0110)	0.0945*** (0.00709)	0.133*** (0.0147)	0.128*** (0.00962)
On 2nd Ave	-0.437*** (0.0561)	-0.182*** (0.0260)		-0.208** (0.0341)	
Constr. Period × On 2nd Ave				0.0484 (0.0299)	0.0142 (0.0185)
Constr. Period				0.0649*** (0.0146)	0.0603*** (0.0101)
Observations	44,299	44,299	44,299	44,299	44,299
R ²	0.0710	0.662	0.766	0.664	0.767
Controls	NO	YES	YES	YES	YES
Building FE	NO	NO	YES	NO	YES

Notes: The dependent variable is log house price. Post is an indicator variable for the period after January 1st 2013. Constr. Period is an indicator variable for the construction period between January 1st 2007 and December 31, 2012. On 2nd Ave is an indicator variable for a unit located in the Second Avenue Corridor as defined in the main text. Controls include: an indicator variable for a condo transaction; number of bedrooms; number of bathrooms; the floor of the building; an indicator variable for built before 1942; an indicator variable for built within 10 years of sale; distance to Central Park; distance to Grand Central Terminal; indicator variables for building amenities (doorman, bike room, gym, elevator, laundry room, concierge, live-in super, pool, storage room, roof deck, children's playroom, parking); as well as indicators if the control variables are missing. Standard errors, clustered at the Census Block, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

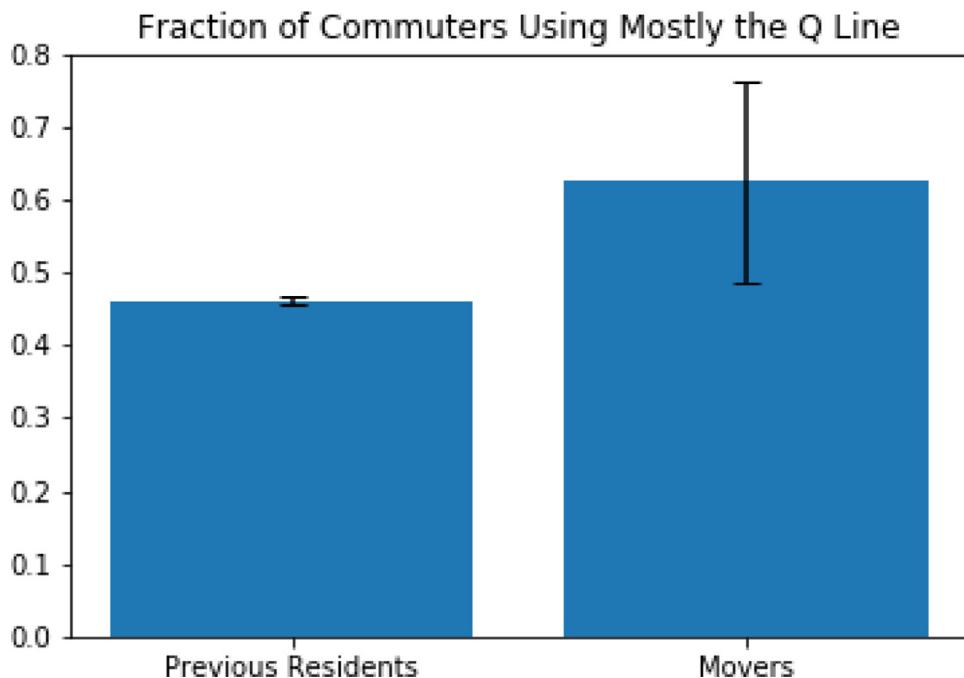


Fig. 4. Subway impact on commuting.

for instance, the coefficient on Post is 0.0575 on log price. This suggests that the post-period is associated with a price premium of $\exp(0.0575) - 1 = 5.9\%$. This variable accounts for the general increase in valuation of UES apartments. The Treat coefficient captures the value differential associated with being “On 2nd Avenue” in general. This effect is quite negative. Properties in the 2nd Avenue corridor generally transact for 35.4% less than properties in the control group, i.e., in the rest of the UES, before considering controls.

The key coefficient of interest is that on the interaction effect “Post × On 2nd Ave.” This coefficient measures the differential price impact of being on the 2nd Avenue corridor after 2013, the time period when subway completion was either imminent or achieved. This pe-

riod captures at least some of the anticipatory effects of subway completion on real estate values, namely those between January 1st 2013 and subway opening on January 1st of 2017. It also contains the subsequent price effects in 2017, 2018, and the first quarter of 2019. The coefficient on the interaction term in column 1 suggests that the 2nd Avenue Subway resulted in a statistically significant and economically large price rise of 12.2% for properties transacting on the avenue ($\exp(0.116)-1$). This number suggests that the construction of the subway was associated with a substantial value creation. We observe convergence in prices: subway construction closes over 1/3 of the gap in valuations between the 2nd Ave corridor and the rest of the UES ($0.122/0.354=0.34$).

Our main specification is reported in column 2. It adds a number of important controls to account for the differences in unit and building characteristics documented above. Controls include: an indicator variable for a condo transaction, an indicator variable for a studio, categorical variables for the number of bedrooms (1BR, 2BR, 3BR, 4 + BR), the number of bathrooms, the floor of the building, the year of construction, the distance to Central Park (an important recreational amenity), the distance to Grand Central Terminal (an important central business district), and indicators for the various building amenities described above; as well as indicators if the control variables are missing. These control variables boost the R^2 value from 7.1% in column 1 to 66.2% in column 2. The lower coefficient (in absolute value) of “On 2nd Ave” indicates that about half of the unconditional difference in valuations between the treatment and control group is accounted for by different average characteristics. However, the estimate of Post \times On 2nd Ave remains large and precisely estimated at $\exp(.0773) - 1 = 8\%$. It indicates even faster convergence of property prices than in column 1: nearly 1/2 of the price difference between 2nd Ave properties and properties in the rest of the UES is eliminated around the time of subway completion.

One possibility is that there are additional property characteristics beyond those included in column 2, and unobserved to us, that matter for real estate values. We capture constant latent differences across neighborhoods and buildings by including building fixed effects in column 3 of Table 3.⁵ This specification compares transactions in the same building before and after the subway.⁶ Adding building fixed effects in column 3 increases the R^2 to 76.6%. In this specification, property values are 3.4% higher on Second Avenue in the Post relative to the Pre period and relative to the control group. The estimate is significant at the 5% level and remains economically large.

6.2. Additional anticipation effects

We consider the possibility of additional anticipation effects as far back as 2007, the year when the decade-long subway construction endeavor began. We include an indicator variable “Constr. Period” which takes the value of 1 for transactions between January 2007 and December 2012, allowing for six more years of potential anticipation effects. This being also the period of heaviest construction, it is plausible that this period experienced a reduction in property values due to disamenities (noise, pollution, closure of retail) related to construction activity. The interaction effect of “Constr. Period \times On 2nd Ave” estimates the net effect of additional anticipation and disamenities on prices in the 2nd Ave corridor, relative to the omitted category of 2003–06. The coefficient on “Constr. Period” shows the general price level on the entire UES during this period, relative to the omitted category of 2003–2006. Under this specification, the “Post \times On 2nd Ave” coefficient measures the price change between the period 2013–2019 and the earlier period 2003–2006 (rather than relative to 2003–2012 in columns 1 and 2). Column 4 of Table 3 shows that the construction period was associated with a substantial increase in real estate values in general on the UES. Prices were 6.7% higher in real terms in 2007–12 relative to 2003–06, after controlling for property characteristics. Properties on the 2nd Ave corridor appreciated by 5% more than properties in the control group over this period. The point estimate is statistically significant and demonstrates the presence of additional anticipation effects, strong enough to outweigh the disamenity effects from construction.

In the Post period, properties on 2nd Ave are 10.8% more valuable than in 2003–06, relative to the control group. In sum, subway construc-

⁵ The coefficient on the treatment variable is not separately identified from the building fixed effects so we drop it in the specifications with building fixed effects.

⁶ We have enough power to identify most building fixed effects; 92% of observations are in buildings that contain at least five transactions in the Pre period and at least five transactions in the Post period.

tion triggered an initial appreciation of 5% in 2007–12 and a further appreciation of 5.8% (10.8% – 5%) in 2013–2019.

Figure 5 illustrates this result graphically under our baseline treatment specification. We show the coefficient estimates from a dynamic difference-in-differences specification on the log of sales price, in which each calendar year is allowed to have its own treatment effect. We see positive price coefficients that are stable around 10% in the construction period of 2007–2012. The price effects grow stronger after 2013, and are especially large in 2016–2018, a period centered around subway opening. This helps alleviate the concern that other trends are driving the effect. The graph also illustrates that our results are not sensitive to various choices of demarcation between Pre and Post periods between 2007 and 2015. By the end of the sample in 2019.Q1, the treatment effect ceases to grow, suggesting that the market has largely priced in the full impact of subway construction. Finally, the graph shows that there are no pre-trends; the estimated effects for 2004–2006 is zero.

In column 5 of Table 3, we add building fixed effects to the specification of column 4. The early anticipation effect during the construction period is smaller at 1.5% but is no longer statistically precisely estimated. Property values in the Post period are 4.2% higher than in the 2003–06 period on 2nd Avenue compared to the control group. This is an economically and statistically significant difference.

6.3. Separating anticipation from construction disamenity effects

To separate anticipation effects from construction disamenities during the construction period, it is useful to look at the rental market. Rents better reflect the current housing market situation since they are not, or at least much less, forward-looking compared to house prices. We perform a series of difference-in-difference estimations for rents in which the Post and Post \times Treat variables are gradually shifted in time. The demarcation between Pre and Post is as early as 2007 in the first regression, then shifts by one year, etc., and is as late as 2018 in the last regression. Panel A of Fig. 6 reports the Post \times Treat coefficient estimates for this series of DiD estimations of log rent. We find small effects when comparing the period before and after 2007, 2008, or 2009. We find much larger effects on rents when comparing rents before and after 2010, 2011, ..., 2015. This is consistent with there being substantial disamenities from construction early on—recall the heavy construction phase started in 2007—which dissipated as heavy construction finished. Those negative rent effects during the heavy construction phase loom large when the post period is defined as all years from 2007 onwards, dragging down the estimated treatment effect. In contrast, when the demarcation line is 2012, all the negative effects on rents due to subway construction are located in the pre-period while the benefits are in the post-period, resulting in large difference-in-differences estimates. The declining pattern for the later years suggests that there were some anticipation effects, even in the rental market, for example due to improved neighborhood amenities (e.g., a new Whole Foods supermarket) in anticipation of the subway opening.

We contrast the rent effects with dynamic price effects in Panel B of Fig. 6. In contrast to the decreased rental coefficients, we observe relatively higher price coefficients during the construction years. We interpret the price coefficients as reflecting both future rents as well as possible shifts in discount rates, and discuss both of these channels in Appendix Section A.5. The contrast between the rental and price coefficients points to important construction disamenity effects which affect rents more than prices during the construction period in particular.

6.4. Unpacking the control group

In Table 4, we revisit our main specification but unpack the control group into its constituent corridors. The omitted corridor is the Madison Ave corridor (spanning from Fifth Ave to Park Ave), so that all changes are measured relative to that Madison Ave corridor. Since this corridor is the farthest removed from the 2nd Ave subway and since it contains

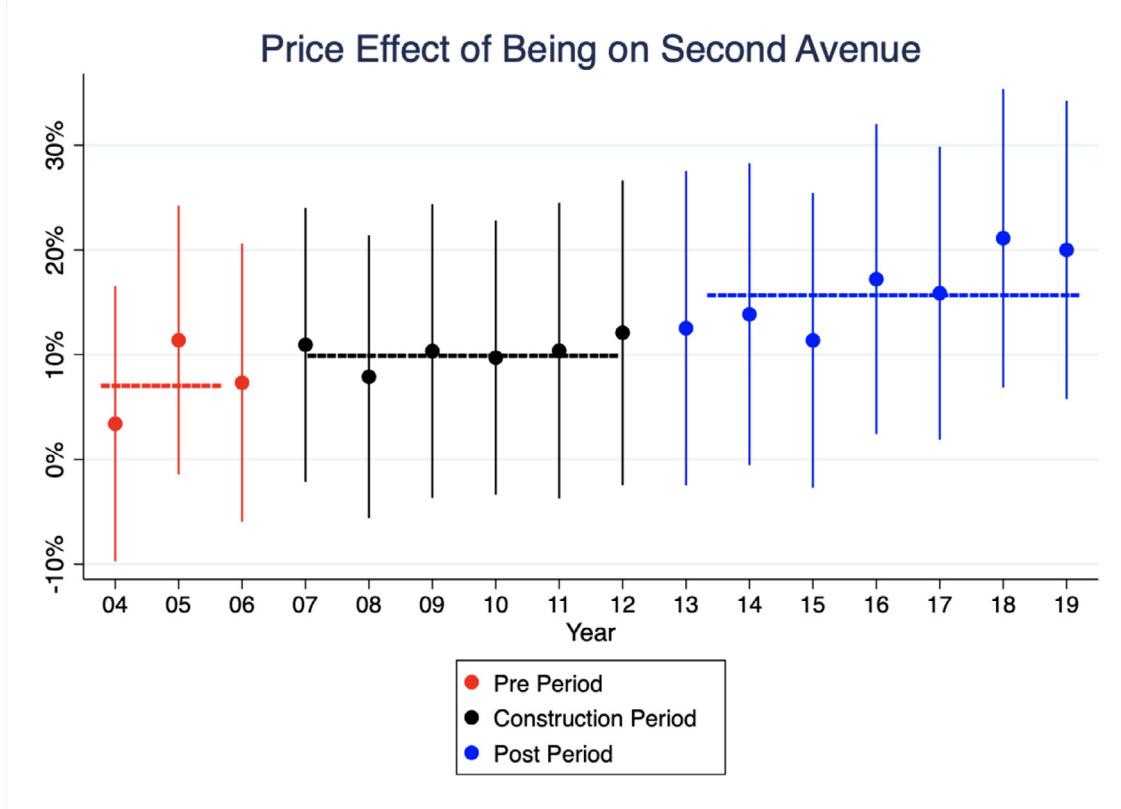
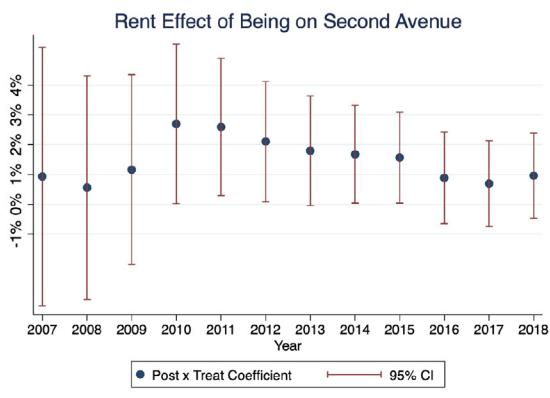


Fig. 5. Dynamic treatment effects - baseline treatment.

Panel A: Rents



Panel B: House Prices

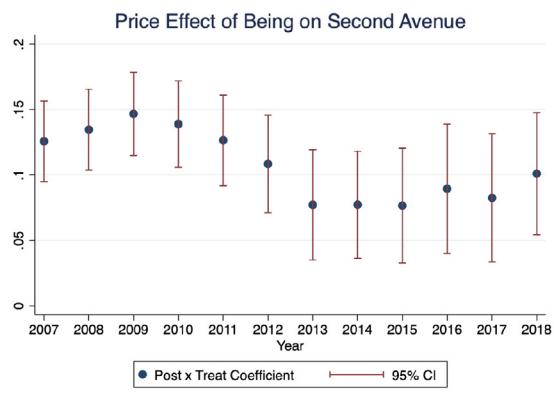


Fig. 6. Disentangling disamenity and anticipation effects.

very wealthy residents who are less likely to use public transportation, this is a natural choice for the omitted category. Column 1 shows that property prices in the pre period (after controlling for building and unit characteristics) were the lowest on 2nd Ave, closely followed by York Ave, then Lex Ave, and highest on Madison Ave (omitted category).

We continue to see our main treatment effect: prices appreciate by 8.9% more in the 2nd Ave corridor in the Post period relative to the Madison Ave corridor.

In contrast, we see no change for the Lexington Ave corridor property valuations. The null effect on Lexington Ave has two possible interpretations. Either there are no spillover effects from the subway construction on the Lexington Avenue corridor, or the positive and negative spillover effects exactly cancel out. The no-spillovers explanation may

make sense given that there is already a subway under Lexington Ave, the 4-5-6 train, which runs parallel to the Q train and offers a much better commuting choice for nearly all residents. But we cannot rule out the alternative explanation of offsetting positive and negative effects. Positive price effects could arise because: (i) the Q train offers a better commuting option for some Lexington Ave residents, (ii) the 4-5-6 train becomes less congested after the Q train construction, or (iii) new restaurants open up within walking distance of Lexington Ave. Negative effects on property prices could arise because of: (i) reduced amenities on Lexington Ave, such as restaurant closures due to increased competition from Second Ave restaurant openings, or (ii) increased competition in the real estate market from newly attractive Second Ave properties. Whichever of these two possibilities is the correct explanation, it does

not affect the value capture numbers below since we estimate a null effect for Lexington Ave. This also further justifies the inclusion of Lexington Avenue in the control group and alleviates concerns of major spillover effects.

The York Avenue corridor sees a substantial 3.9% price change. The estimate is about half as large as the treatment effect for the 2nd Ave corridor and is significant at the 1% level. This evidence suggests that York Ave may have been at least partially affected (treated) by the subway extension. We study this possibility in more detail below in alternative treatment definitions in which York Avenue properties belong to the treatment group.

Column 2 adds building fixed effects. It finds a 3.0% price gain on Second Ave relative to Madison Ave, and no price gain on Lexington Ave nor on York Ave.

The last two columns consider the specification with the construction period broken out. Column 3 shows a strong 11.2% capital gain on 2nd Ave, relative to Madison Ave and relative to the pre-construction era of 2003–06. The gain of 3.9% in the construction period underscores early anticipation effects. Lexington Ave shows no change in either period, relative to Madison. Property prices on York Ave do not appreciate in the 2007–12 period relative to Madison Ave, but catch up relative to Madison Ave in the Post period, for a combined effect of 3.4%. Finally, in column 4, we add building fixed effects. While the post-period real estate capital gain remains at 2.3% the construction-era effect disappears.

6.5. Alternative treatment definitions

6.5.1. Distance to new stations

One drawback of our baseline definition of treatment is that we assume that all properties along the 2nd Avenue Corridor are equally treated by new subway construction. This may not be the case if areas far from the subway stops, along 2nd Ave, do not find much of a benefit from using the new subway. To analyze this possibility, we consider a second treatment definition which includes all properties within 0.3 miles of one of the three new 2nd Avenue subway stops.⁷ If these properties 0.3 miles benefit the most from the subway construction, they should expect the greatest property price appreciation. But, disamenities from construction may also have been greatest closest to the subway stops.

Table 1 refers to this alternative treatment definition as “Treatment2”. It shows that 80.6% of the transactions on the 2nd Avenue corridor and 21.6% of the transactions in the Madison, Lexington, and York Ave corridors fall within 0.3 miles of one of the new subway stations. In other words, this treatment is strongly but not perfectly correlated with our baseline treatment. **Fig. 3**, Panel B shows the treated and control buildings. The 0.3-mile distance requirement traces diamond-shaped areas around the three new subway stations.

Columns 1 and 2 of **Table 5** revisit our main difference-in-differences estimation for this alternative treatment definition and for our preferred specifications with building and unit controls, and with building fixed effects. We find a strongly positive and statistically significant increase in value due to the subway for those properties that are within 0.3 miles of one of the three new Q-line stations. The headline increase is 5.6%, while the increase with building fixed effects is 2.8%. The corresponding numbers for the baseline treatment were 8% and 3.4%. This comparison suggests that properties in the 2nd Avenue corridor that are not within 0.3 miles from a new station benefitted slightly more from the subway than properties in the Lexington Ave or York Ave corridors that are within 0.3 miles of a new 2nd Ave subway station.

Further investigation, reported in Appendix **Table A2**, breaks down the treatment group into transactions that are between 0 and 0.10 miles,

between 0.10 and 0.20 miles, and between 0.20 and 0.30 miles from a new Q-line station. The overall 5.6% price gain results from a large and precisely estimated gains of 7.9% in properties between 0.2 and 0.3 miles away from the station and 4.3% in properties between 0.1 and 0.2 miles away. The gain closer by is 1.1% and not significant. The analysis also shows a small price decline closest to the station during the construction period. This is exactly where we expect the disamenities from construction to show up. In contrast, prices in the 0.2–0.3 mile ring appreciate 9.1% during the construction period and an additional 4.2% (for a total effect of 13.3%) in the Post period.

6.5.2. Closest subway station becomes closer

We explore a second alternative treatment definition which places greater weight on peripheral properties which experienced large gains in transit access. For every apartment in our sample, we compute the distance to the nearest subway station on any line serving the UES, both before and after the addition of the three stations on the Second Avenue subway line (8 stations in total). Distance is calculated as walking distance based on Google Maps taking into account that each station has multiple entrances.

Table 1 reports that for the average unit in the 2nd Ave corridor, the closest station was 0.32 miles away before the Q-line extension and 0.18 miles after, for an average distance reduction of 0.14 miles (225 meters). For the residents of the other three corridors in Panel B, the average reduction was smaller at 0.07 miles (113 meters). The latter is the combination of a zero reduction for all residents of the Madison corridor and most residents of the Lexington corridor, on the one hand, and a large reduction for the residents on the York Ave corridor, on the other hand. We define an apartment as treated if there is a strictly positive distance reduction to the nearest subway station on the UES. **Table 1** refers to this alternative treatment definition as “treat3”. It shows that 78.9% of the transactions in the 2nd Avenue corridor and 32% of the transactions in the Madison, Lexington, and York Ave corridors are in a building which experiences a reduction in distance to the nearest station. Again, this treatment is strongly but not perfectly correlated with our baseline treatment. **Fig. 3**, Panel C shows the treated and control group buildings according to this second alternative treatment definition. The largest change with the baseline and this alternative treatment is that nearly all properties in the York Avenue corridor are now treated.

Columns 3 and 4 of **Table 5** shows the difference-in-differences estimates. For our main specifications, we find a similar effect from the subway extension: 5.5% without and 0.8% with building fixed effects.⁸

Further investigation, reported in Appendix **Table A3**, breaks down the treatment group into units that experienced a reduction in distance (i) between 0 and 0.10 miles, and (ii) greater than 0.10 miles. The latter group consists mostly of units east of 2nd Ave. The 5.5% overall price effect is the average of 12.1% estimated gains in the former group, and 2.7% in the latter group. Both are significant at the 1% level. While one might think that properties experiencing a larger reduction in distance are “more intensively” treated, the data suggest that the gains are largest for those who experience a modest reduction in distance. For some far east residents, it is possible that the 2nd Ave subway remains too far away to be useful. Alternate transportation options may dominate even after the new subway becomes available. Also, properties close to the East River are 8.3% more expensive in the Pre period, suggesting a wealthier clientele that may have lower utilization of public transportation in the first place. Nevertheless, even the 2.7% price gain is substantial and helps to put in context the York Ave results presented above.

⁷ Distance is defined by walking distance as calculated by Google Maps. For each of our buildings, we feed in the street address into the Google Maps API and obtain the distance to each subway station entrance (multiple per station) on the UES, to Central Park, and to Grand Central Terminal.

⁸ We have also repeated this analysis on a subsample of properties within 0.5 miles from a subway stop, assuming that these properties are most likely to be within walking distance of public transit. The results are slightly stronger for this subsample than for the full sample, but very similar given that 96% of properties satisfy this restriction.

Table 4
Unpacking the control group.

	(1)	(2)	(3)	(4)
Post × On 2nd Ave	0.0854** (0.0269)	0.0296 (0.0169)	0.106** (0.0397)	0.0225 (0.0256)
Post × On Lexington Ave	-0.00606 (0.0262)	-0.00283 (0.0187)	-0.0126 (0.0336)	-0.0241 (0.0241)
Post × On York Ave	0.0382 (0.0273)	-0.00690 (0.0166)	0.0333 (0.0399)	-0.0295 (0.0254)
Constr. Period × On 2nd Ave			0.0381 (0.0368)	-0.0153 (0.0273)
Constr. Period × On Lexington Ave			(0.0318) (0.0318)	(0.0268) (0.0268)
Constr. Period × On York Ave			-0.011 (0.017)	-0.045*** (0.015)
Post	0.0904*** (0.0199)	0.0980*** (0.0137)	0.131*** (0.0268)	0.147*** (0.0197)
On 2nd Ave	-0.430*** (0.0574)		-0.451*** (0.0617)	
On Lexington Ave	-0.216*** (0.0378)		-0.209*** (0.0425)	
On York Ave	-0.360*** (0.0840)		-0.355*** (0.0876)	
Constr. Period			0.0745** (0.0261)	0.0897*** (0.0222)
Observations	44,299	44,299	44,299	44,299
R ²	0.667	0.766	0.670	0.767
Controls	YES	YES	YES	YES
Building FE	NO	YES	NO	YES

Notes: The dependent variable is log house price. “Post” is an indicator variable for the period after January 1st 2013. “Constr. Period” is an indicator variable for the construction period between January 1st 2007 and December 31, 2012. Control variables are the same as in Table 3. Standard errors, clustered at the Census Block, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5
Difference-in-differences estimates: Alternative treatment definitions.

	(1)	(2)	(3)	(4)	(5)	(6)
Post × Treat	0.0542* (0.0210)	0.0272* (0.0113)	0.0537* (0.0206)	0.00843 (0.0118)	0.0642** (0.0238)	0.0286* (0.0126)
Post	0.102*** (0.0127)	0.0952*** (0.00754)	0.0970*** (0.0133)	0.103*** (0.00867)	0.108*** (0.0114)	0.0994*** (0.00696)
Treat	-0.140*** (0.0287)		-0.133*** (0.0376)		-0.168*** (0.0299)	
Observations	44,299	44,299	44,299	44,299	44,299	44,299
R ²	0.659	0.766	0.656	0.766	0.660	0.766
Controls	YES	YES	YES	YES	YES	YES
Building FE	NO	YES	NO	YES	NO	YES
Treatment Def.	2	2	3	3	4	4

Notes: The dependent variable is log house price. “Post” is an indicator variable for the period after January 1st 2013. “Treat” is an indicator variable which takes on the value of 1 if a transaction is in the treatment area. The table considers three alternative treatment definitions, as indicated in the last row. Columns 1 and 2 use treatment definition 2 which takes the value of 1 for a transaction located within 0.3 miles of one of the three new subway stations on the Second Avenue subway and 0 otherwise. Columns 3 and 4 use the change in distance definition (treatment 3) which is 1 for a transaction located in an area that experienced a change in distance to the closest station after the Second Avenue subway and 0 otherwise. Columns 5 and 6 use the all of the above definition (treatment 4) which is 1 for a transaction located in treatment areas 1, 2, and 3 and 0 otherwise. Controls are the same as in Table 3. Standard errors, clustered at the Census Block, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6.5.3. All of the above

A final alternative treatment definition combines the first three treatments. We consider a unit treated if it is treated under all three previous definitions. This treatment isolates properties on the 2nd Ave corridor, close to a new subway station, for which one of the new stations is the closest subway option (i.e., there is a distance reduction). Table 1 reports that 72.7% of units on the 2nd Ave corridor satisfy this requirement (“treat4”) and none of the units on the other corridors, by construction. About 28.2% of the overall sample receives this combination treatment. Fig. 3, Panel D shows the treatment and control groups according to the combination treatment definition.

Columns 5 and 6 of Table 5 show the difference-in-differences estimates. For our main specifications, we find a 6.6% and 2.9% subway effect, both of which are precisely estimated. In conclusion, the analysis in this section confirms large and robust estimated effects from the Q-line subway extension.

6.6. Heterogeneous treatment and supply response

Though our results suggest substantial effects of the Q-line construction on prices on average, we also consider the possibility that the subway extension had different effects on newer buildings. We define

Table 6
Heterogeneous treatment for new vs. old buildings.

	(1)	(2)	(3)	(4)
Post × Treat	0.0709** (0.0215)	0.0530** (0.0203)	0.0361 (0.0199)	0.0559* (0.0229)
Post × Treat × New Constr.	0.0855 (0.115)	0.125 (0.111)	0.291** (0.0951)	0.130 (0.103)
Post × New Constr.	-0.137 (0.0985)	-0.168 (0.0991)	-0.292** (0.0951)	-0.155 (0.0805)
Post	0.0900*** (0.0101)	0.0933*** (0.0118)	0.0969*** (0.0135)	0.101*** (0.0110)
Treat	-0.194*** (0.0257)	-0.154*** (0.0286)	-0.152*** (0.0390)	-0.182*** (0.0300)
New Constr.	0.357*** (0.0371)	0.347*** (0.0434)	0.345*** (0.0432)	0.353*** (0.0376)
Observations	44,299	44,299	44,299	44,299
R ²	0.656	0.654	0.651	0.654
Controls	YES	YES	YES	YES
Building FE	NO	NO	NO	NO
Treatment Def.	1	2	3	4

Notes: The dependent variable is log house price. "NewConstr." is an indicator variable which is 1 for units in buildings constructed in 2003 or later and zero otherwise. All other variables are as in Table 3. Each column uses an alternative definition of the treatment area, as highlighted in the last row of the table. The alternative treatment definitions 2, 3, and 4 are the same as in Table 4. Standard errors, clustered at the Census Block, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

newer buildings to be those constructed after January 2003. The categorical variable "NewConstr" isolates transactions in these buildings. Table 1 shows that 6.8% of units transacted in the treatment group are in newer buildings compared to 4.4% in the control group. Table 6 estimates the triple interaction effect "Post x Treat x NewConstr." We find a 8.9% larger appreciation for units in newer buildings in the treatment area after subway construction than for older buildings. The appreciation is 7.3% for older buildings and 16.2% for newer buildings. The additional 8.9% is precisely estimated despite the relatively small share of transactions in buildings built after 2003. The remaining columns of Table 6 show an even larger treatment effect for recently constructed units when using the alternative treatment definitions. The treatment effect for units built before 2003 remains statistically and economically large in all specifications, however. In sum, one channel through which the 2nd Ave subway has resulted in convergence in real estate values between the 2nd Ave subway corridor and the rest of the UES is by promoting the development of new residential units. Units in newer buildings trade at a substantial premium to existing units, as can be seen in the $\exp(0.357) - 1 = 42.9\%$ estimate on "NewConstr." While the new-building premium fell substantially in the Post period in the control group (-12.8%), it fell much less in the treatment group (-12.0% + 8.9% = -3.1%). A larger prevalence of new units on the 2nd Ave corridor contributes to the convergence.⁹

Motivated by this result, we investigate further whether the 2nd Ave subway extension triggered a housing supply response in Appendix A.4. We obtain data on net changes to the housing stock between 2010 and 2020 and units in new buildings that received certificates of occupancy (COO units) between 2000 and 2019. The former measure accounts for demolition while the latter measure is available over a longer period. A difference-in-differences analysis for COO units indicates about 150 additional housing units supplied annually in the treatment area after 2013.

We explore a second source of heterogeneity in the treatment effect. Appendix Table A4 reports treatment effects by apartment size, mea-

⁹ This result also sheds light on the lower treatment estimates in the specification with building fixed effects compared with the main specification with building characteristics. There are fewer transactions in new buildings that occur both before and after subway construction, limiting our sample.

sured as the number of bedrooms. The omitted category is units with zero bedrooms (studios). We find significant treatment effects across all apartment sizes but the percentage gains are monotonically increasing in the size of the apartment: around 5.8% for one-bedroom units rising to 20.1% for 2BR, 26.1% for 3BR, and 48.9% for units that have four or more bedrooms. The estimates are similar for all four treatment definitions.

The results in this section suggest that gains were unequally distributed and were strongest for larger and newer housing units.

6.7. Repeat sales

In Table 7, we perform a repeat-sales analysis. This commonly used approach in real estate valuation compares the prices of properties with the previous price paid for the same property. It has the virtue of holding (most) unit characteristics constant. It has the well-known limitation that we are only able to analyze properties that do, in fact, repeatedly transact in this period. We have 14,144 repeat sales, representing only 31.9% of the total number of transactions, confirming a large reduction in sample size. Column 1 repeats the earlier analysis (main specification with controls) on the subset of apartments that transact at least twice.¹⁰ The repeat-sales sample features a smaller estimate of the baseline treatment effect: a 2.6% value creation estimate from the subway extension compared to a 8% effect for the full sample. In other words, this one-third subsample with repeat transactions displays a baseline treatment effect that is one-third as large as the full-sample estimate. This baseline repeat-sales estimate of 2.6% is quite close to the 3.3% estimate in the main sample's specification with fixed effects, which is reassuring.

With that new baseline estimate in mind, column 2 adds the log residual sale price of the previous transaction of the same unit, i.e., from the first leg of the repeat sale. This residual sale price is the unexplained component from a regression of the log sale price on Post, Treat, Post × Treat, and controls. This procedure removes the subway effect from the transaction price paid in the first leg of the transaction. The residual contains all other unmeasured unit and building characteristics that impact valuation. The lagged residual price enters strongly significantly with a coefficient around 0.6 and boosts the regression R² from 74.0% to 87.2%. The last six columns repeat the same two specifications for the three alternative treatment definitions. In all cases, we continue to find significant treatment effects with point estimates on Post × Treat between 2.4% and 5.9%. In sum, controlling for additional unit characteristics via repeat sales results in robust baseline gain estimates.

6.8. Contrasting price effects and commuting estimates

Before continuing on to an analysis of rental prices and valuation ratios, we perform a simple analysis connecting our estimates on the reduction in commuting time with our estimates on the house price impact. While the value of commuting presents a lower bound on the welfare gains from subway construction, it provides a useful starting point to understand the scope of value generated.

Recall that we observed 5–10% price increases for properties in our treatment area (the median treatment property in our sample is worth \$845,036), while subway construction lowered one-way commutes by 3 minutes. These estimates correspond to \$14,000–\$28,000 increases in house prices per minute of commute saved. While apparently large, these estimates correspond closely to estimates drawn from

¹⁰ When determining whether a transaction in our 2003–2019 dataset is a repeat sale, we look for transactions in StreetEasy before January 2003 to avoid selection on properties that transact twice within the 2003–2019 time frame. Despite limited data coverage prior to 2003, this results in several hundred additional repeat sales included in the analysis. Also, if a property is the subject of two (or more) repeat sales, both (all) repeat-sales transactions for which the second leg of the trade pair is in our sample period 2003–2019 enter the repeat sales sample.

Table 7
Repeat sales subsample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × Treat	0.0259 (0.0221)	0.0233 (0.0130)	0.0368 (0.0226)	0.0233* (0.0116)	0.0569* (0.0223)	0.0302* (0.0120)	0.0238 (0.0226)	0.0270* (0.0121)
Post	0.0985*** (0.0136)	0.0441*** (0.00858)	0.0903*** (0.0147)	0.0418*** (0.00923)	0.0781*** (0.0159)	0.0361*** (0.0100)	0.101*** (0.0130)	0.0448*** (0.00797)
Treat	-0.149*** (0.0251)	-0.169*** (0.0137)	-0.135*** (0.0281)	-0.146** (0.0132)	-0.125*** (0.0365)	-0.130*** (0.0192)	-0.135*** (0.0279)	-0.163*** (0.0139)
Lagged Price Resid	0.644*** (0.0134)		0.646*** (0.0132)		0.651*** (0.0134)		0.647*** (0.0136)	
Observations	14,144	14,144	14,144	14,144	14,144	14,144	14,144	14,144
R ²	0.740	0.872	0.739	0.872	0.735	0.872	0.738	0.872
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Building FE	NO	NO	NO	NO	NO	NO	NO	NO
Treatment Def.	1	1	2	2	3	3	4	4

Notes: This is the subsample of sales transactions for which we observe a prior transaction in the data. The lagged log price residual is the residual from a first-stage regression of the log price in the first transaction of the repeat-sales pair on Post, Treat, Post × Treat, and controls. Standard errors, clustered at the Census Block, are in parentheses.

** p<0.01, ** p<0.05, * p<0.1.

other sources on the gradient between commuting into NYC and house prices. The *New York Times* estimates, for instance, that shorter commuting times along the Metro North light rail line heading into Grand Central Station result in higher house prices with a range from about \$10,000 to \$36,000 per minute in commute time saved.¹¹

An alternate back-of-the-envelope calculation contrasting house price incorporates the value of time saved. A typical resident of the UES earns \$100,000 per year, works 2000 hours, and has an hourly wage of \$50/hour. If this individual saves 3 minutes for each commute completed five days a week, for 50 weeks out of the year—the corresponding value of time saved is \$1,250 per year. As this value accrues every year into the future, it can be valued as a perpetuity. Using a discount rate of human capital of $r = 2.5\%$, as estimated by Lustig et al. (2013), results in a value of time saved of \$50,000. This is close to the baseline estimated capital gain for apartments on the UES of \$70,000 (8.0% of \$845,036), and closer still to some of the smaller gains in the specifications with fixed effects or repeat sales.

While these estimates ignore the various benefits of transit expansion which are capitalized in the price yet not measured through work commutes alone, they illustrate the general plausibility of our findings. The price gains we observe seem generally in line with the transit improvements, and suggest large real estate price gains from alleviating commute lengths.

7. Rental and valuation analysis

7.1. Rents

The real estate value creation effects from the subway extension, found in the prior analysis, not only manifest themselves in price gains on owner-occupied units but also in rent increases in rental buildings. We use the universe of rental listings to repeat the difference-in-differences analysis on log asking rents. We include the same, long list of property and unit characteristics to control for observable differences in order to isolate the subway effect. One caveat to this analysis is that the data set contains asking rents not contract rents. To the extent that this creates measurement error, it would attenuate the coefficient of interest. We only include one rental observation per unit-year to avoid double-counting repeated listings of the same unit. The final sample contains 99,034 rental unit-year observations.

Columns 1 and 2 of Table 8 show the treatment estimates for the rental sample. In column 1, we repeat the main specification from the

sales analysis, with the Post period starting in 2013 and controls included. We find that rents are 1.8% higher on the 2nd Ave corridor in the Post period. This rental increase closes nearly 1/3 of the 6.19% gap in rent levels between the 2nd Ave corridor and the rest of the UES. The effect is economically large and precisely estimated.

In column 2, we redefine the Post period as the period after January 1, 2017. This date marks the opening of the subway. In this specification, we find annual rents that are 0.69% higher in our main treatment area. The effect is precisely estimated. Comparing columns 1 and 2, we find some anticipation effects in the rental market as well. This is consistent with tenants that expect to stay for multiple years and move in anticipation of the subway opening. It is also consistent with a rebound in local area amenities (e.g., street-level retail) after 2013, which were temporarily depressed during the heavy construction phase from 2007 to 2012.

Rental data are useful to better disentangle the disamenity and anticipation effects during the construction period. The rental market is a spot market, and hence subject to fewer anticipation effects. Exploiting the timing of rent versus price increases, Appendix 6.3 establishes that disamenities from construction were important.

7.2. Valuation ratios

Next we turn to valuation ratios. When forming price-rent ratios, it is important to compare similar units that are for sale and for rent. This is feasible in a dense urban neighborhood like the UES where both owner- and renter-occupied units are prevalent, often of similar type and quality, on nearly every block.

To construct the log price-rent ratio in a given tax block and year for a comparable property, we first estimate separate regressions for log prices and log rents on a full set of tax block × year fixed effects and full set of control variables, using our sales transactions and rental listing data sets, respectively.¹² We then subtract the block-year fixed effect, estimated from the log price regression, from the corresponding block-year fixed effect, estimated from the log rent regression, to form the log price-rent ratio for each block-year. We sort tax blocks into Treatment and Control areas based on their location, using our main treatment definition.

We then regress the log rent, the log price, and the log price-rent indices at the tax block level on Post, Treat, Post×Treat, and controls for distance to Central Park and to Grand Central Terminal. In columns

¹¹ <https://www.nytimes.com/2017/03/17/realestate/how-much-is-your-house-worth-per-commuting-minute.html>.

¹² We omit the controls distance to Central Park and distance to Grand Central Terminal in these first-stage regressions since these controls are not separately identified from the block-year fixed effects.

Table 8
Rentals: difference-in-differences results - baseline treatment definition.

VARIABLES	(1) Log R	(2) Log R	(3) Log R	(4) Log P	(5) Log P/R	(6) Log R	(7) Log P	(8) Log P/R
Post × Treat	0.018* (0.009)	0.007 (0.007)	0.028* (0.015)	0.049*** (0.019)	0.021 (0.023)	0.023* (0.014)	0.078*** (0.021)	0.055** (0.025)
Post	0.032*** (0.007)	0.008* (0.005)	0.007 (0.011)	0.079*** (0.013)	0.072*** (0.016)	-0.003 (0.010)	0.052*** (0.014)	0.054*** (0.017)
Treat	-0.060*** (0.016)	-0.050*** (0.013)	-0.110*** (0.023)	-0.189*** (0.028)	-0.079** (0.030)	-0.100*** (0.020)	-0.179*** (0.026)	-0.079*** (0.027)
Observations	99,034	99,034	1789	1789	1789	1789	1789	1789
R ²	0.807	0.806	0.397	0.434	0.084	0.395	0.419	0.073
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Building FE	NO	NO	NO	NO	NO	NO	NO	NO
Post Year	2013	2017	2013	2013	2013	2017	2017	2017
Treatment Def	1	1	1	1	1	1	1	1

Notes: The dependent variable in columns 1 and 2 is log asking rents at the unit level. The dependent variable in columns 3 to 8 are log rents, log prices, and log price/rent ratios at the tax block level. Log rents (log prices) at the tax block level are obtained as the fixed effects in a first-stage regression of log rents (log prices) of individual apartment units on tax block × year fixed effects and a vector of unit and building controls, except for distance to Central Park and to Grand Central. ‘Controls’ indicate different control variables in each specification. In columns 1 and 2, the controls refer to the same unit characteristics used for our main regressions with sales data. In columns 3–8, controls refer to the tax block-level distance from Central Park and Grand Central Station. Standard errors, clustered at the Census or Tax Block, are in parentheses.

3–5 of Table 8 the Post period is post-2013, while in column 6–8 the Post period is post-2017. Since the analysis is at the block level, there are fewer observations (1,789) and consequently less power. The earlier regressions of log price and log rent at the unit level already established significance, so that we can focus on economic magnitudes for this exercise.

The observed log change in the price-dividend ratio equals the estimated DiD effect on prices minus the DiD effect on rents. Using 2013 as the demarcation between the before and after periods, the estimate in column (5) of Table 8 indicates a change in the price-rent ratio of 2.1% points while the estimate in column (8) indicates a 5.5% point change.

The asset pricing (Campbell and Shiller, 1988; Cochrane, 2011) and real estate literatures (Campbell et al., 2009; Plazzi et al., 2010; Van Nieuwerburgh, 2019) strongly suggest that variation in the price-rent ratio reflects not only variation in expected rental growth but also, and mostly, variation in expected future returns. Appendix A.5 sets up such a present-value model to conceptualize the effect of the subway on the difference in risk premia and expected growth rates between treatment and control areas.

That appendix explains that the 2.1% (5.5%) change in the price-rent ratio either indicates a reduction in the relative risk premium on residential real estate in the treatment area of 2.1% (5.5%) points per year, or an increase in the relative expected rental growth rate in the treatment area of 2.1% (5.5%) points per year, or a combination of the two whose sum (in absolute value) is 2.1% (5.5%) points per year. In light of the literature’s findings that the price-rent ratio predicts future returns at least as much as it predicts future rent growth, we think it most plausible that the subway both lowered the riskiness of real estate investment and increased its long-run cash flow growth potential. The finding that infrastructure investment lowers risk in real estate markets is novel to the literature, and points to an interesting complementarity between infrastructure and real estate investments.

7.3. Gentrification and the marginal buyer

One potential driver for the lower expected returns on real estate is that the marginal buyer of real estate in the treatment area may have changed after the subway extension. For example, if the marginal buyer has lower risk aversion or lower risk, measured by a lower correlation of her consumption growth with house price growth or a lower volatility of consumption growth, then the expected return would fall relative to the pre-period. Appendix A.6 shows that newcomers’ income in the

treatment area rises after subway construction. While the data is too sparse to establish statistical significance, it is directionally consistent with gentrification resulting in a change in the marginal resident. We also find evidence in Appendix A.7 that the subway expansion increased the number of home sales in the treatment area. This additional turnover is likely due—in part—to new residents arriving in the area.

8. Value capture

In this section, we take our baseline estimates for the value created by the subway based on the observed transactions and use them to compute the aggregate value creation for the stock of residential real estate on the UES. We then use property tax data to compute how much of this value creation flows back to the city in the form of higher taxes. We find that while there is an overall gain, the government’s ability to recoup these expenses depends critically on the ability to tax real estate. Our analysis abstracts from the specific government entity responsible; we implicitly assume that one local government bears construction costs and earns future property tax revenues. We abstract from fare revenues, other tax revenue sources such as greater sales or income tax revenue, and costs of operating and maintaining the new subway line and stations. Our focus is on the scope for property taxation to recover the cost of project investment.

8.1. Baseline valuation of the stock of real estate

We start by valuing the stock of real estate in the treatment area in the period before subway construction. We choose 2012 as a base year, the last year of our “Pre” period. This stock consists of owner-occupied residential real estate, renter-occupied residential real estate, and commercial real estate.

8.1.1. Owner-occupied residential buildings

Imputing the value of owner-occupied residential real estate occurs in three steps.

Step 1: Transacted Units

For each apartment in the baseline treatment area (2nd Ave corridor) for which we observe at least one sale, we use the dynamic difference-in-differences specification with controls to impute an annual valuation for the year 2012. The imputation uses the actual apartment unit and building characteristics alongside the estimated coefficients. Since the

regression specification includes a condo indicator variable, valuation differences between coop and condo units are taken into account.

Step 2: Other Units in Coop Buildings with Transactions Even though we observe more than 16 years of transactions in a liquid market, many coop units never transact in our sample. Based on building-level data, we know how many units there are in each coop building and therefore what fraction f of units we are missing. We obtain the valuation of the entire building by multiplying the cumulative value of the units for which we have trades by $1 + f$. The underlying assumption is that the average characteristics of the missing coop units are the same as those of the transacted units.

Step 3: All Other Units Based on a master list of all tax identifiers (Borough-Block-Lot or BBL codes) from the New York City Department of Finance, we obtain a list of all condo units and coop buildings in the Second Avenue corridor and their 2012 “estimated market value” (EMV). After comparing this master list against our transactions data, we obtain the BBLs for which we see no transactions. Each condo unit has its own BBL whereas all units in a coop building share the same BBL. For each condo unit and coop building valued in steps 1 and 2, we calculate an EMV multiple. The EMV multiple is the ratio of our 2012 valuation to the 2012 EMV in the tax roll data. We then average the EMVs separately for condos and coops and for each tax block. There are 83 tax blocks in our Second Avenue treatment area. The 2012 value of a missing condo unit is its 2012 EMV from the city records times the average EMV multiple for condos in that tax block. The value of a missing coop building is the 2012 EMV for that coop building times the EMV multiple for coop buildings in that tax block.

8.1.2. Renter-occupied buildings

Next, there is a large stock of rental buildings to consider. After all, the home ownership rate on the UES is only 41%. For each unit in our rental building sample, we obtain a 2012 value by combining its own unit and building characteristics and the dynamic difference-in-differences coefficients, estimated from the condo and coop transactions.¹³ To obtain the total value of the building, we scale up the cumulative value of the transacted units by $1 + f$, where f is the fraction of missing units in the building.

For every rental building thus valued, we compute the EMV multiple as the ratio of our 2012 valuation to the city’s 2012 EMV. We average the EMV ratios for rental buildings by tax block. We value the rental buildings (BBLs) for which we have no StreetEasy rental data by multiplying their EMV from the tax roll data by the EMV multiple for rental buildings in that tax block. Our valuation approach is consistent with New York City’s Department of Finance approach which values all owner-occupied buildings as if they were rental buildings.

8.1.3. Commercial properties

The final property type is commercial, non-residential real estate: retail, office, and industrial properties. Since the 2nd Ave corridor is largely a residential neighborhood, this type of real estate is a less important part of the overall real estate stock. The dominant type of commercial real estate is street-level urban retail (shops and restaurants), followed by parking garages. Since we observe very few transactions of commercial properties and lack sufficient building characteristics for the transactions we do observe, we exclusively use the EMV approach. We use the 2012 EMV for each commercial BBL. To obtain a market value, we multiply the commercial EMV by a tax-block specific EMV ratio. The tax-block’s EMV ratio is the average of the EMV ratios for condo, coop, and rental BBLs in that tax block. The approach assumes that the 2012 EMV ratio is the same for commercial and residential real estate in a given tax block. If the true EMV ratio is higher (lower) for

¹³ We set the condo indicator variable equal to 0.5, assuming that rentals are valued at the average of coops and condos. This assumption makes almost no quantitative difference to our valuation.

commercial than for residential real estate for most tax blocks, then we obtain a downward (upward) biased estimate of the total value of real estate in the Second Avenue corridor.

As shown in the first column of [Table 9](#), we estimate the total 2012 market value of real estate in our treatment area at \$69 billion across the three categories of real estate.

8.2. Tax pass-through

To assess the amount of property taxes that typically passes through to the city government in response to property appreciation, we make use of tax assessment records for New York City. For owners of condos and coops, the city assess property taxes on a portion of the property’s market value, the so-called assessed value. This assessed value is automatically tied to income earned on similar rental properties, and is calculated using several steps.

First, the city calculates a property’s Estimated Market Value (EMV) by dividing an estimate of the annual Net Operating Income (NOI) by the cap rate (an estimate of the ratio of NOI to price):

$$\text{EMV} = \frac{\text{NOI}_{\text{comparables}}}{\text{Cap Rate}}.$$

The NOI is estimated using the property’s square footage, multiplied by the average NOI per sq. ft. of comparable units, typically three buildings that are geographically close to the building in question, of similar size and vintage. The cap rate was set uniformly at 12.42% in January 2018. The true market cap rate at that time was around 4%, so that the EMV is about three times smaller than the actual market value.

Next, the city estimates the property’s assessed value, which is set at 45% of the EMV. Finally, owners pay a tax rate of 12.9% on the assessed value minus any exemptions. Absent exemptions, the tax rate is 5.8% of EMV. Changes in property taxes—due to changes in NOI of comparable rental buildings—are gradually phased in over a five year period. While we do not observe tax exemptions, we have tax paid in 2015 for all properties. This data suggests a non-trivial role for exemptions, and indicates that actual tax paid is 4.8% of EMV.

To understand how the subway construction affects tax revenue, we start with a simple example for the typical condo building in the 2nd Ave corridor. Suppose a building has 90 units, and a total of 140,000 sqft. Suppose the true market value is \$175 million, or \$1,250 per sqft. Given a NOI of \$50 per sqft, this valuation corresponds to a 4.0% cap rate. The EMV is based on a 12.42% cap rate and so is \$37.65 million, or \$269 per sqft. The assessed value is 45% of EMV or \$16.94 million. This becomes \$14 million after the 17.5% condo abatement, a common form of exemption. Annual tax paid is \$1.8 million for the building or \$20,000 per unit, which is 4.8% of EMV and 1.0% of true market value.

Suppose now that the 2nd Ave subway increases the value of this building by 8%, the (exponentiated) point estimate in column 2 of [Table 3](#), or \$14 million. The EMV increases by \$3 million, and the assessed value by \$1.36 million. Taxes paid will increase annually by \$144,155 in year 5 and beyond, and gradually be phased in before that. Assuming a government discount rate of 3%, corresponding to NYC’s municipal bond yield, the subway results in \$4.44 million in extra tax revenue in present value terms. The estimate of value capture, or how much of the price increase accrues to the city government is \$4.28m / \$14.00m = 30.6%. This pass-through estimate is not far from the nationwide average long-run elasticity of property tax revenue to house prices, estimated at 0.4 by [Lutz \(2008\)](#).

We adopt this 30.6% pass-through estimate to calculate the additional present value tax revenue increase NYC may expect due to the Second Avenue extension. The first row of [Table 9](#) shows the estimated log change in market value across our main specifications from [Table 3](#), repeated for convenience. The second row exponentiates these numbers to obtain percentage changes. Rows 3–5 apply these percentage gains to the estimated 2012 market value of real estate in our treatment area,

Table 9
Estimates of value creation.

Value Add Under:	Value in 2012 (in bn \$)	(2) Standard Controls	(3) Building FE	(4) Constr. Period	(5) Constr. Period + Building FE
Treatment Effect:		0.077*** (0.043)	0.033** (0.021)	0.103** (0.012)	0.041* (0.019)
Percentage Change:		8	3.4	10.8	4.2
Owner-Occupied Residential (\$b)	31	2.52	1.06	3.41	1.32
Renter-Occupied Buildings (\$b)	26	2.05	.86	2.77	1.07
Commercial Non-residential (\$b)	12	0.95	0.4	1.28	0.5
Total Value Created (\$b):	69	5.53	2.32	7.46	2.89
Property Tax Receipts (\$b):		1.69	0.71	2.28	.88
Net Gain to Govt (\$b):		(2.81)	(3.79)	(2.22)	(3.62)

per the calculations detailed above. The assumption is that the value gain from subway construction was uniform across property types.

We estimate that the subway construction led to a total value increase of \$5.53 billion in our benchmark specification. For different specifications in columns 3–5, estimates range between \$2.32 for the fixed-effect specification (column 3) and \$7.46 billion for the specification with separate construction period (column 4). However, the city is able to capture only 30.6% of this value in the form of higher taxes. This table displays our estimates of the amount captured by the city government in present value terms from increased property taxation in the row “Property Tax Receipts.” The baseline specification predicts a \$1.69 billion increase; the other specifications produce estimates ranging from \$0.71 to \$2.28 billion. We contrast these numbers with the construction cost of \$4.5 billion, and show in the last row the shortfall in revenue. The baseline estimate is a \$2.81 billion public shortfall. Even though the value generated from subway construction was substantial enough to exceed the (very large) subway construction cost, the gains largely accrued to private owners of condo and co-op units and landlords managing rental and commercial real estate properties. Focusing on the property tax revenue, the city suffered a substantial shortfall, especially under the more conservative value gain estimates.

We perform two additional robustness checks on our core estimation. The first, in [Appendix A.8](#), uses the results from the corridor specification in [Table 4](#) to assess value creation. This exercise results in a larger real estate value creation and property tax capture. The resulting difference with the cost of subway construction narrows from the baseline -\$2.8 billion to -\$2.1 billion.

Second, as discussed briefly above and in detail in [Appendix A.4](#), the subway expansion may also have caused additional construction of apartment buildings. The data on the net new supply of housing units (additions minus demolitions) and data on new certificates of occupancy (COO) suggest a very modest subway-induced supply response. If we ignore the loss of units due to demolition and assume that all 840 units that received COOs in the treatment area between 2013 and 2019 are fully attributable to the subway, then the cost gap would be lower by \$0.22–0.36 billion.

Both exercises suggest that our main estimate of the cost gap is conservative and similar across approaches.

8.3. Value capture through micro-targeted property taxes

Our paper demonstrates that it is technically feasible to determine how much each housing unit benefited from the new transit infrastructure, taking into account its exact location, and its unit and building characteristics. In theory, local government could levy a unit-specific property tax surcharge proportional to the value created. Such micro-targeted property tax surcharges would be based on objectively measurable value increases and property characteristics, and hence be fair. They could become an important financing tool to fund future infrastructure needs.

Strikingly, nearly all of our estimates of the value gain from the Second Ave Subway construction itself exceed the cost of construction. Our estimates suggest that while the cost of construction of the subway is quite high, so is the value creation, at least in densely-populated areas such as the Upper East Side.

Two caveats are in order. First, it may be politically difficult to levy micro-targeted property taxes. Second, it is an empirical question how large the elasticity of tax revenue is to increases in property taxes. [Haughwout et al. \(2004\)](#) provide evidence that property prices fall in response to higher property tax rates. They find that New York City was close to the peak of its tax revenue hill in the late 1990s. The extent to which these estimates are still relevant thirty years later is an open question.

An additional impact of value capture taxes in this context may be the role of selection on local residents. The subway construction may attract some buyers who do not value the subway *per se*, but instead hope to take advantage of capital gains by reselling to future buyers who do value the subway. To the extent that value capture taxes limit the capital gains, this may potentially concentrate the buying population to those residents who value the subway as an amenity. As we discuss in [Appendix Section A.6](#), the household income among residents who move into the area is slightly higher after subway construction, consistent with the subway’s construction appealing to a different population.

8.4. Value capture in practice

While the Second Avenue expansion included no explicit value capture elements, a literature examines different value capture instruments in other contexts. In Hong Kong, the Mass Transit Railway (MTR) corporation enjoys development rights in the vicinity of transit stops which may be sold to private developers in exchange for a fraction of the profits. In Tokyo, a variety of private and semi-private transit companies internalize the spillover benefits of transit projects by purchasing and developing land prior to constructing station stops to certain areas. In these Asian cities, real estate development accounts for a large share of overall transit revenue ([Murakami, 2012](#); [Calimente, 2012](#); [Medda, 2012](#)).

Even in New York City itself, the 7 train extension to Hudson Yards used an innovative financing formula. The train extension was financed by a \$3 billion bond issuance by a special purpose vehicle, the Hudson Yards Infrastructure Corporation (HYIC). To ensure bond repayment by the HYIC, it received property tax payments from private developers as well as revenues from the sale of additional construction rights enabling developers to exceed zoning limits ([Petretta, 2020](#)). These examples illustrate the viability and growing acceptance of value-capture methods to fund transit projects around the world, including in New York City.

9. Conclusion

Mass public transit is a critical infrastructure asset in dense urban environments, but construction costs have risen substantially. To justify

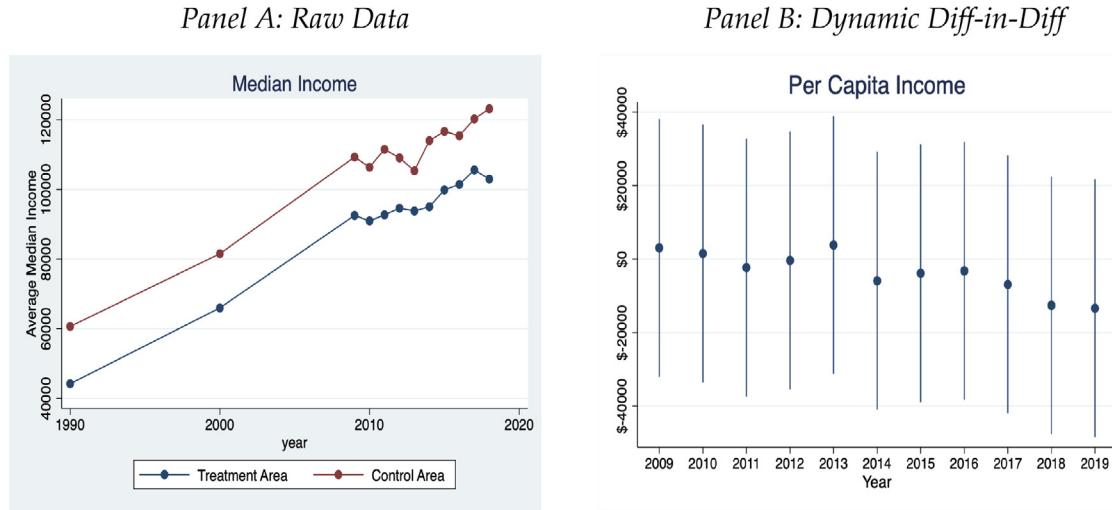


Fig. A1. Income upper east side residents.

further expansion, transit must demonstrate significant returns either directly or through the capitalization of externalities in real estate prices. Exploiting one of the most expensive investments ever made in one of the oldest and largest subway systems in the world, the Second Ave subway extension in New York City, we find evidence of such capitalization using a difference-in-differences framework. This extension cost \$4.5 billion to build, one of the most expensive projects of its type, making it an ideal setting whether the benefits from this construction can justify the expense. Our data set allows us to control finely for building and unit characteristics. Our estimates suggest price appreciation of 5–10% across specifications. Much of the value gain occurs in anticipation of the subway opening.

Using new mobile phone location data, we document substantial improvements in commuting lengths, which are concentrated among individuals who live near the new subway stations and take the subway. Q-line subway usage is also higher among new residents, suggesting that the composition of residents was also affected by the subway construction. Such migrants are likely marginal buyers and renters in the area. The commuting results provide one plausible channel for the price effects.

We also find significant increases in rents that are consistent with the capitalization effects. Increases in price-rent ratios in the treatment area reflect not only higher rents but also lower risk premia on real estate brought about by the infrastructure investment.

Valuing the total stock of treated real estate at \$69 billion pre-treatment, our baseline estimate suggests a \$5.53 billion gain from the 2nd Ave subway extension to private landlords. We estimate that the city will only recoup about 30% of the gain, or about \$1.69 billion, in the form of future property taxes. The former number well exceeds the \$4.5 billion cost of the project, while the latter number falls significantly short. This suggests that additional taxation, in the form of targeted property tax increases, might be useful to help finance public infrastructure projects. More broadly, value capture could prove a useful instrument in the financing tool box to help fund the large future infrastructure needs.

Appendix A

A1. Resident income

From the IPUMS data set, we obtain per capita income for each census block group in Manhattan for the 1990 and 2000 Census and for each five-year American Community Survey between 2005–2009 and 2015–2019. Next, we use geographic shape files of Manhattan to classify each

census block group as being within the UES, and within the UES in the Second Avenue Corridor (Treatment) or outside of it (Control). We keep only observations from block groups in the UES that we have in each survey to obtain a balanced panel. The left panel of Fig. A1 plots the raw income data. We then estimate a dynamic DiD regression for per capita income. Fig. A1 plots the coefficients on $Treat \times Year$. The omitted/baseline year is 2000. The results confirm the parallel pre-trends. They also show a treatment effect for per capita income that is not statistically different from zero no matter what year is considered to be the first post-subway year. The evidence suggests that incomes in treatment and control areas grew at the same rate between 2000 and 2019.

A2. Cell phone data

We show representativeness of the VenPath device population in several ways in Fig. A2. In Panel A, we plot the relationship between the Census population and the mobile phone population measured for the same ZIP code. We measure device population the same way as in our commute analysis by focusing on individuals with a sufficient presence at night-time to be designated as local residents. While the mobile phone population is a sample of the broader population, so that we do not have 100% coverage, we still measure a substantial correlation of 0.781 between the two measures, indicating that our sample does appear to be broadly representative of the population in general.

Panels B–D explore whether the mobile phone representativeness varies based on local demographics. We correlate the fraction of the local population which can be measured as a mobile phone resident against various demographic characteristics at the ZIP-level. We find minimal association between device representativeness and the fraction of residents who are white (-0.048), and also a minimal association (0.022) between device representativeness and the fraction of young (18–45 year-olds) individuals. We observe a slightly higher correlation (0.196) between device representativeness and the fraction of locals with a Bachelor's degree. We conclude that our device population appears to be fairly representative, including in the important dimensions of race and age. We may be slightly oversampling more educated individuals who may be more likely to use smartphones.

A3. Additional house price results

Tables A1–A4 contain additional results on house prices, as discussed in the main text.

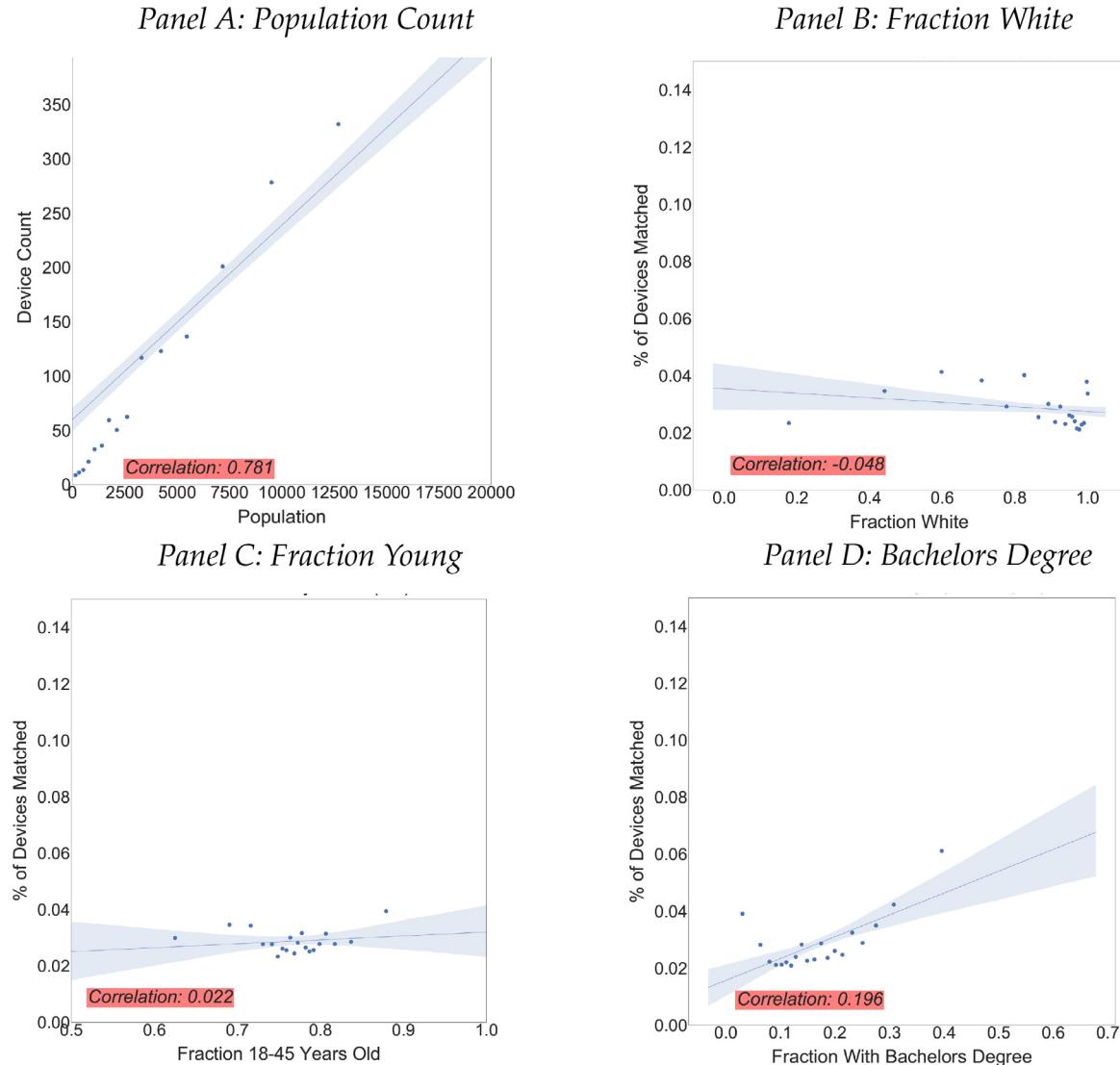


Fig. A2. Representativeness of mobile phone data.

A4. Supply response

This appendix investigates more thoroughly the extent to which the subway extension led to an increase in the supply of housing units in the treatment area. We explore various data sources and methods. The overall picture that emerges is one of only very modest new construction.

Units by Year Constructed Fig. A3 reports the number of apartments constructed by year of construction. It combines information in our sales data on the year of construction of the building, the number of units in the building, and the location of the building. We focus on buildings built between 2003 and 2019. We observe 8 buildings constructed in both treatment and control areas between 2007–2012 (4 each in treatment and control), and 10 buildings built between 2013–2019 (5 each in treatment and control). This suggests that there was no larger differential construction response in the treatment area in the post period.

Zoning Changes

There were no major zoning changes in the treatment area during the Second Avenue subway construction period. From an inspection of the NYC list of zoning changes, we found only three minor zoning changes around the three new Q train stations during the construction period: A small sidewalk café near the 86th street station in 2009, one 36-story

mixed use building around the 96th street station in 2013, and one 63-story mixed use building around the 96th street station in 2017. There was a major neighborhood rezoning passed for the East Harlem area in 2017 allowing for construction of additional dense housing, but only a small part of East Harlem is part of the Second Avenue Corridor.

Net Change in Housing Stock

The NYC Department of Planning publishes data on the *net* change in housing units for the 2010–2020 period. The data accounts not only for new construction, but also for alterations and demolitions. In a brief based on these data, NYC reports significant net housing losses within our treatment area and much of the rest of the UES over this decade. At the community district level, the UES zone had the second lowest net housing growth of any community district in NYC.

Census tracts in the treatment area experienced a net housing growth of 452 new units cumulatively over the 2010–2020 period. This compares to a gain of 569 net housing units in the tracts located in the control area. Panel A of Fig. A4 plots the breakdown of net new units by year. The level of both variables is extremely low relative to the total housing stock of the UES, and smaller for the treatment than the control area in the raw numbers.

We can estimate a housing supply elasticity from these numbers. The net gain of 452 units in the treatment area between 2010 to 2020 is a

Table A1
Main price effects - alternate clustering.

	(1)	(2)	(3)	(4)	(5)
Post × On 2nd Ave	0.116 (4.55)	0.0777 (4.03)	0.0331 (2.50)	0.104 (3.59)	0.0411 (2.07)
Post	0.0571 (2.03)	0.0970 (2.91)	0.0945 (3.11)	0.132 (2.70)	0.128 (2.85)
On 2nd Ave	-0.437 (-8.02)	-0.182 (-7.21)		-0.209 (-6.85)	
Constr. Period × On 2nd Ave			0.0500 (2.02)	0.0142 (0.75)	
Constr. Period			0.0645 (1.25)	0.0603 (1.17)	
Observations	44,196	44,196	44,196	44,196	44,196
R ²	0.0709	0.663	0.765	0.665	0.766
Controls	NO	YES	YES	YES	YES
Building FE	NO	NO	YES	NO	YES

Notes: The dependent variable is log house price. Post is an indicator variable for the period after January 1st 2013. Constr. Period is an indicator variable for the construction period between January 1st 2007 and December 31, 2012. On 2nd Ave is an indicator variable for a unit located in the Second Avenue Corridor as defined in the main text. Controls include: an indicator variable for a condo transaction; number of bedrooms; number of bathrooms; the floor of the building; an indicator variable for built before 1942; an indicator variable for built within 10 years of sale; distance to Central Park; distance to Grand Central Terminal; indicator variables for building amenities (doorman, bike room, gym, elevator, laundry room, concierge, live-in super, pool, storage room, roof deck, children's playroom, parking); as well as indicators if the control variables are missing. Standard errors are two-way clustered at the Census Block and year level, and t-statistics are shown in parentheses.

Table A2
Within distance broken down.

VARIABLES	(1) Log Price	(2) Log Price	(3) Log Price	(4) Log Price
Post × Within 0 – 0.1 mi	0.0112 (0.0222)	0.00493 (0.0183)	0.00987 (0.0291)	0.00342 (0.0223)
Post × Within 0.1 – 0.2 mi	0.0423 (0.0268)	0.0119 (0.0146)	0.0486 (0.0327)	0.0104 (0.0209)
Post × Within 0.2 – 0.3 mi	0.0762** (0.0286)	0.0444** (0.0150)	0.125* (0.0481)	0.0536* (0.0233)
Constr. Period × Within 0 - 0.1 mi		-0.00265 (0.0265)	-0.00265 (0.0218)	
Constr. Period × Within 0.1 - 0.2 mi		0.00958 (0.0267)	-0.00497 (0.0212)	
Constr. Period × Within 0.2 - 0.3 mi		0.0868 (0.0452)	0.0132 (0.0228)	
Post	0.101*** (0.0127)	0.0951*** (0.00754)	0.136*** (0.0183)	0.130*** (0.0112)
Constr. Period			0.0645*** (0.0179)	0.0638*** (0.0121)
Within 0 – 0.1 mi	-0.150*** (0.0301)	-0.148*** (0.0364)		
Within 0.1 – 0.2 mi	-0.137*** (0.0347)	-0.145*** (0.0409)		
Within 0.2 – 0.3 mi	-0.138*** (0.0358)	-0.187*** (0.0477)		
Observations	44,299	44,299	44,299	44,299
R ²	0.659	0.766	0.662	0.767
Controls	YES	YES	YES	YES
Building FE	NO	YES	NO	YES

gain of 0.76% on a 2010 housing stock of 59,027 units. We divide this by our baseline price gain estimate of 8%: $0.76 \div 8.0 = 0.095$. Therefore, we estimate a supply elasticity of 0.1% for the UES.

Table A5 investigates this more formally. This Table explores two dependent variables as supply outcomes. The first is net new units drawn from the NYC Department of Planning, shown in the first two columns. Column 1 reports a DiD of net new units measured at the tract-year level, and the second column collapses at the area-year level (treatment vs. control) in the second column as dependent variables. We find no

Table A3
Change in distance broken down.

VARIABLES	(1) Log Price	(2) Log Price	(3) Log Price	(4) Log Price
Post × Chg. dist 0-0.10mi	0.114** (0.0383)	0.0402 (0.0205)	0.166** (0.0598)	0.0654 (0.0358)
Post × Chg. dist > 0.10mi	0.0264 (0.0188)	-0.00408 (0.0114)	0.0215 (0.0239)	-0.0103 (0.0149)
Constr. Period × Chg. dist 0-0.10mi			0.102 (0.0560)	0.0467 (0.0369)
Constr. Period × Chg. dist > 0.10mi			-0.0120 (0.0205)	-0.0135 (0.0147)
Post	0.0975*** (0.0132)	0.103*** (0.00867)	0.136*** (0.0176)	0.138*** (0.0107)
Constr. Period			0.0711*** (0.0146)	0.0632*** (0.0115)
Chg. dist 0-0.10mi	-0.189*** (0.0500)	-0.244*** (0.0687)		
Chg. dist > 0.10mi	-0.0900* (0.0371)	-0.0863* (0.0384)		
Observations	44,299	44,299	44,299	44,299
R ²	0.657	0.766	0.659	0.767
Controls	YES	YES	YES	YES
Building FE	NO	YES	NO	YES

Table A4
Heterogenous treatment effect by number of bedrooms.

VARIABLES	(1) Log Price	(2) Log Price	(3) Log Price	(4) Log Price
Post × Treat	-0.0480* (0.0209)	-0.0591* (0.0260)	-0.0514* (0.0257)	-0.0417 (0.0256)
Post × Treat × 1BR	0.0564* (0.0219)	0.0613* (0.0256)	0.0403 (0.0237)	0.0438 (0.0262)
Post × Treat × 2BR	0.187*** (0.0288)	0.150*** (0.0294)	0.157*** (0.0278)	0.159*** (0.0324)
Post × Treat × 3BR	0.232*** (0.0414)	0.185*** (0.0371)	0.177*** (0.0406)	0.215*** (0.0505)
Post × Treat × 4BR +	0.398*** (0.0786)	0.345*** (0.0654)	0.323*** (0.0734)	0.388*** (0.0910)
Treat × 1BR	-0.0396 (0.0327)	-0.0590 (0.0338)	-0.0997** (0.0361)	-0.0523 (0.0341)
Treat × 2BR	-0.168*** (0.0398)	-0.138*** (0.0404)	-0.252*** (0.0415)	-0.170*** (0.0421)
Treat × 3BR	-0.285*** (0.0491)	-0.235*** (0.0459)	-0.321*** (0.0535)	-0.305*** (0.0588)
Treat × 4BR +	-0.301** (0.0915)	-0.257** (0.0822)	-0.321*** (0.0799)	-0.360*** (0.0995)
Post	0.0985*** (0.0109)	0.102*** (0.0126)	0.0982*** (0.0131)	0.108*** (0.0113)
Treat	-0.0641 (0.0356)	-0.0237 (0.0371)	0.0473 (0.0393)	-0.0421 (0.0369)
1BR	0.348*** (0.0251)	0.361*** (0.0260)	0.397*** (0.0288)	0.355*** (0.0224)
2BR	0.751*** (0.0263)	0.756*** (0.0281)	0.831*** (0.0304)	0.748*** (0.0241)
3BR	1.101*** (0.0333)	1.113*** (0.0363)	1.179*** (0.0376)	1.094*** (0.0305)
4BR+	1.183*** (0.0333)	1.190*** (0.0363)	1.252*** (0.0376)	1.194*** (0.0305)
Observations	44,299	44,299	44,299	44,299
R ²	0.665	0.661	0.659	0.662
Controls	YES	YES	YES	YES
Building FE	NO	NO	NO	NO
Treatment Def.	1	2	3	4

significant relative net housing growth on the Second Avenue subway in 2013–2020 versus the 2010–2013 period.

Certificates of Occupancy

We also obtain data from NYC on the number of new units in buildings with new certificates of occupancy, COO units for short. This data has the drawback of not accounting for alterations and demolitions, but the benefit of a longer sample period (2000–2019). Panel B of Fig. A4 plots the total number of COO units in the treatment and control areas in each year. We observe about 120 additional COO units per year

Table A5
Supply response.

VARIABLES	(1) Net New Units	(2) Net New Units	(3) COO	(4) COO	(5) COO
Post x Treat	-0.433 (8.587)	68.792 (89.509)	0.772 (1.041)	34.410 (33.707)	149.132* (88.235)
Post	-4.597 (4.620)	-124.125* (63.292)	-1.344** (0.621)	-61.725*** (22.095)	-194.901*** (62.392)
Treat	2.135 (7.323)	-60.667 (76.333)	0.282 (0.616)	-4.560 (20.095)	-93.846* (52.201)
Observations	418	22	4500	103	40
R-squared	0.004	0.206	0.001	0.084	0.239

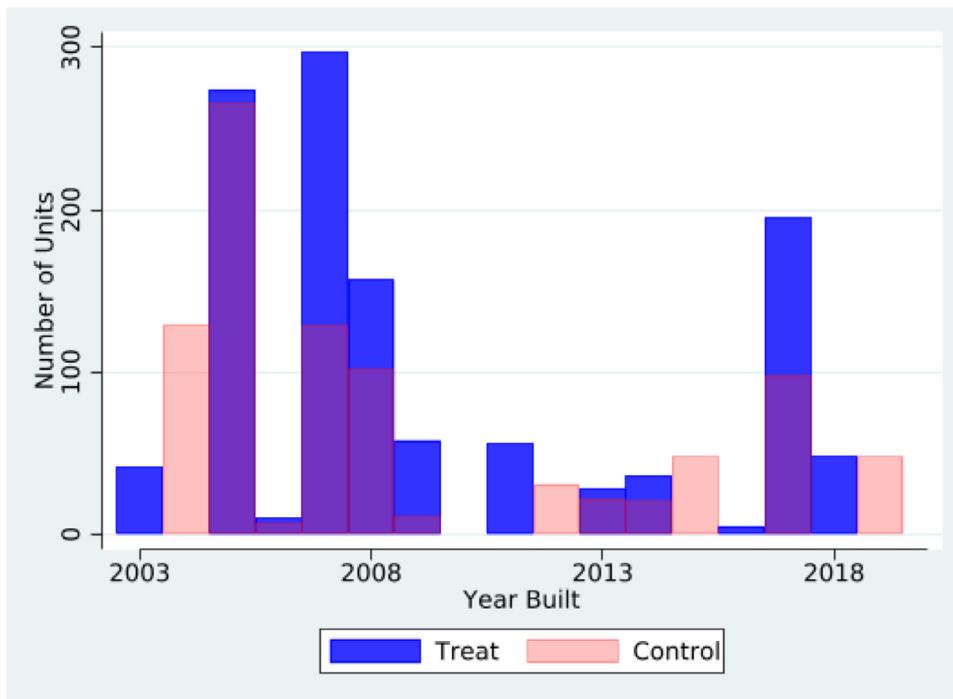


Fig. A3. Number of housing units by construction year.

in treatment areas from 2013–2019, and 65 additional COO units in control areas. While there is a general downward trend in newly constructed units, and the numbers are small, the graph suggests more newly constructed units in the treatment area.

We explore this more formally in a DiD analysis, summing COO units at the tax block-year level in Columns (3)–(4) of Table A5 and at the area-year level in Column (5). Column (4) excludes tax block-years with zero COO units. We find a relative increase of about 150 units per year in the period after 2013 relative to before in the treatment area relative to the control area. The point estimate is statistically significant at the 10% level. This is likely an upper bound on the treatment effect on new construction since demolitions are not subtracted.

Value Capture Calculations Considering New Supply According to the COO data, 840 new units were built in our treatment area between 2013 to 2019. This is roughly 2.7% of the 31,104 unique units we observe in our sales data built in 2012 or earlier. Using our median sale price of \$845,036, this translates into \$0.71 billion worth of real estate value created. Repeating these calculations using the 75th percentile sale price of \$1,405,996 per unit results in an estimate of \$1.18 billion. Assuming that 100% of this construction was driven by the subway expansion, this results in \$217–\$361 million of additional property tax receipts, for the median and 75th percentile cases respectively. Taking into account this upper bound on the value created by new supply in the treatment area, the benchmark number for the net cost of the subway to the government of \$2.81 billion would be lower by \$0.22–\$0.36 billion.

A5. Present-value model

The present-value model of Campbell and Shiller (1989) states that the price-rent ratio today (pd_t) must reflect either the market's expectation of future rent growth (Δd_{t+j}), or expectations of future returns on housing (r_{t+j}), or a combination of the two:

$$pd_t = \frac{k}{1-\rho} + E_t \left[\sum_{j=1}^{+\infty} \rho^{j-1} \Delta d_{t+j} \right] - E_t \left[\sum_{j=1}^{+\infty} \rho^{j-1} r_{t+j} \right]. \quad (4)$$

where the linearization constants k and ρ are functions of the long-term average log price-rent ratio, \bar{pd} :

$$\rho = \frac{\exp(\bar{pd})}{1 + \exp(\bar{pd})}, \quad k = \log(1 + \exp(\bar{pd})) - \bar{pd}. \quad (5)$$

This equation also holds unconditionally:

$$\bar{pd} = \frac{k}{1-\rho} + \frac{\bar{g}}{1-\rho} - \frac{\bar{x}}{1-\rho}, \quad (6)$$

where $\bar{g} = E[\Delta d_t]$ and $\bar{x} = E[r_t]$ are the unconditional expected rent growth and expected return, respectively. Equation (6) can be rewritten to deliver the well-known Gordon Growth model (in logs) by plugging in for k :

$$\tilde{dp} = \log(1 + \exp \bar{pd}) - \bar{pd} = \bar{x} - \bar{g}. \quad (7)$$

The left-hand side variable is approximately equal to the long-run rental yield \bar{dp} , also known as the “cap rate” in the real estate literature.

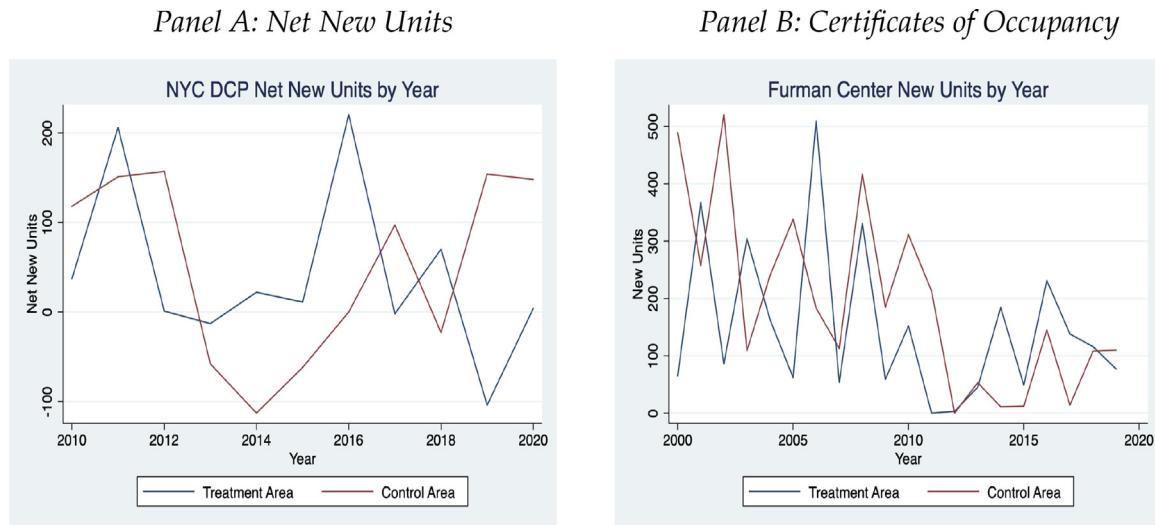


Fig. A4. New housing units constructed.

Note that the Gordon growth model, or the more general Campbell-Shiller model, cannot help distinguish between how much of the variation in price-rent ratios comes from cash flow expectations versus discount rate movements. The price-rent ratio (and more generally the history of prices and rents) only pins down the difference between the two. This is a key identification challenge that is the topic of much work in asset pricing. In the absence of additional data on rental growth expectations or return expectations from surveys, the only option is to make assumptions on one of the terms in order to obtain conclusions on the other term. We pursue this path and consider two extreme cases. In both cases, we assume that the arrival of the subway causes housing markets to change permanently and we consider the old versus the new steady state.

In the first case, the subway did not differentially affect future expected returns in the treatment area compared to the control area. Since the risk-free rate is of course common to the two areas, this amounts to assuming that risk premia did not change differentially between the treatment (T) and control (C) area before (B) versus after (A) the subway construction:

$$\bar{x}_{TB} - \bar{x}_{CB} = \bar{x}_{TA} - \bar{x}_{CA} \Leftrightarrow \Delta \bar{x}_T - \Delta \bar{x}_C = 0,$$

where we use Δ to denote the change over time, i.e., after versus before the subway construction. Note that this assumption still allows for common changes in risk premia over time, as well as level differences in risk premia between treatment and control areas. But it rules out that the subway made real estate investments in the treatment area relatively safer. Under this assumption, the change in the price-dividend ratio in treatment minus control areas identifies the market's expectation about expected future rent growth in treatment minus control area. The difference-in-differences version of Eq. (7) becomes:

$$\Delta \tilde{d}p_T - \Delta \tilde{d}p_C = -(\Delta \bar{g}_T - \Delta \bar{g}_C) \quad (8)$$

In the second case, we attribute all the changes in the price-rent ratio to changes in expected returns, or equivalently in risk premia. The difference-in-differences version of Eq. (7) becomes:

$$\Delta \tilde{d}p_T - \Delta \tilde{d}p_C = (\Delta \bar{x}_T - \Delta \bar{x}_C) \quad (9)$$

This assumes that expected rent growth did not change differentially between the treatment (T) and control (C) area before (B) versus after (A) the subway construction:

$$\bar{g}_{TB} - \bar{g}_{CB} = \bar{g}_{TA} - \bar{g}_{CA} \Leftrightarrow \Delta \bar{g}_T - \Delta \bar{g}_C = 0.$$

Note that this assumption still allows for common changes in rent growth expectations over time, as well as level differences in expected rent growth between treatment and control areas.

The observed log change in the price-dividend ratio equals the estimated DiD effect on prices minus the DiD effect on rents. Using 2013 as the demarcation between the before and after periods, the estimate in column (5) of Table 8 indicates a change in the price-rent ratio of 2.1% points while the estimate in column (8) indicates a 5.5% point change. The 2.1% (5.5%) number either indicates a reduction in the relative risk premium on residential real estate in the treatment area of 2.1% (5.5%) points per year, or an increase in the relative expected rental growth rate in the treatment area of 2.1% (5.5%) points per year, or a combination of the two whose sum (in absolute value) is 2.1% (5.5%) points per year. We think it most plausible that the subway both lowered the riskiness of real estate investment and increased its long-run cash flow growth potential.

A6. Gentrification

Each five-year American Community Survey wave for 2006–2010 to 2013–2017 contains household median income by migration status for each census tract in the UES. We select newcomers to the UES who moved from another Manhattan census tract outside the UES or from outside Manhattan. We split migrants by whether they moved to a tract in the treatment area (indicated by 1) or in the control area (indicated by 0). Fig. A5 shows that the income of the migrants into the treatment area is catching up to that of the migrants into the control area as time goes by.

Table A6 estimates a difference-in-differences specification for median income at the tract-level, using all UES tracts and all eight ACS waves. The first four survey waves are the “Pre” period while the last four waves are “Post” period. Column 1 analyzes median income among all UES residents. Column 2 looks at median income among residents who did not move over the past year. Column 3 looks at residents who moved from elsewhere in Manhattan, while column 4 moved in from elsewhere in New York State. While the standard errors are large given the small number of tracts, the evidence suggests that household income among movers in the treatment area is higher in the Post period (columns 3 and 4). The same is not true for median income among all residents or among stayers (columns 1 and 2). This possibility of subway-induced gentrification is consistent with our results. The increased housing demand and subway utilization among new residents may have contributed to the house price increase and commuting reduction we find. At the same time, we note that the estimated income effects are modest and that the share of movers is modest as well.

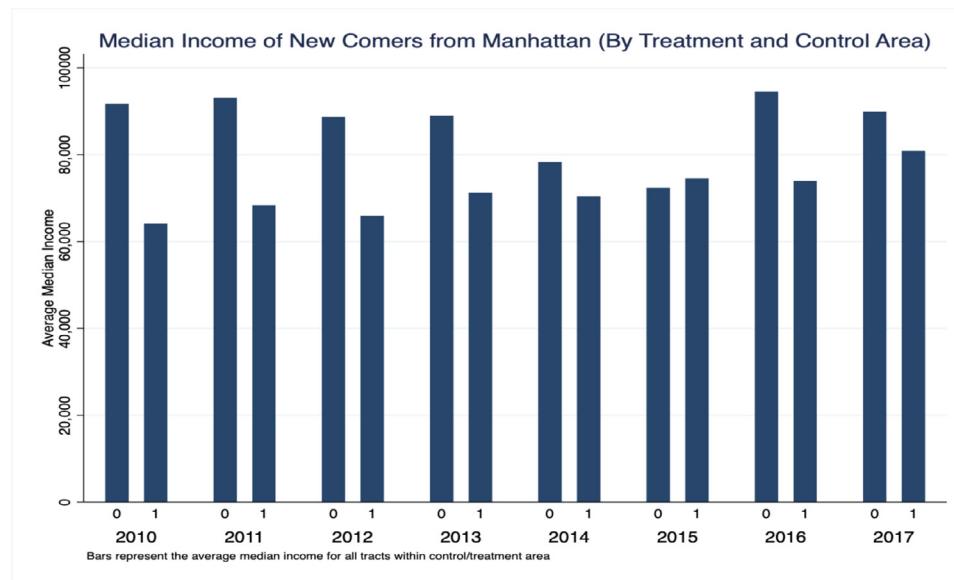
Fig. A5. Income of Migrants into Manhattan.

Table A6
Median income at the tract-level.

Dependent Variable: Selection:	(1) Median Income All	(2) Median Income Residents	(3) Median Income Moved Same County	(4) Median Income Moved NY State
Post x Treat	-1,921 (6,494)	-1,529 (6,892)	1733 (11,128)	1507 (13,399)
Post	6,490*** (2,315)	5,332** (2,464)	5961 (4,107)	5160 (5,447)
Treat	2160 (4,394)	1851 (4,664)	-9,225 (7,382)	-6,058 (8,030)
Observations	585	581	537	397

Table A7
Transaction volume by block year.

VARIABLES	(1) Log Num. Sales	(2) Log Price Volume	(3) Log Num. Sales	(4) Log Price Volume
Post x Treat	0.0539 (0.0811)	0.119 (0.102)	0.125* (0.0701)	0.219** (0.0881)
Post	-0.286*** (0.0481)	-0.171*** (0.0605)	-0.244*** (0.0413)	-0.177*** (0.0518)
Treat	0.100 (0.0709)	-0.442*** (0.0893)	0.0916* (0.0449)	-0.441*** (0.0564)
Observations	3089	3089	3089	3089
R-squared	0.021	0.023	0.018	0.025
Post Year	2007	2007	2013	2013

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

A7. Transaction volume

To estimate the effect of the subway on transaction volume, we collapse our transaction data down to the tax block level and count the number of transactions and total dollar volume of transactions in each tax block-year. We classify each tax block as inside or outside our treatment area (Second Ave corridor). **Table A7** shows the results from the DiD regression for the log number of transactions and log dollar transaction volume. We use both 2007 and 2013 as the demarcation between Pre and Post.

For our benchmark definition of the Post period, which starts in 2013, we find a 12.5% increase in the number of transactions and a

22% increase in the dollar volume. The former effect is significant at the 10% level, while the latter effect is significant at the 5% level. The effects loose statistical significance and are about half as large if we include the subway construction period between 2007 and 2012 in the definition of the Post period, but remain economically meaningful. These results show that the subway created a boom not only in unit prices but also in the number of transactions. The two combined to create a large increase in dollar sales volumes. The increase in sales could reflect higher turnover of the existing housing stock, possibly bringing in new residents who value the subway more than departing residents. Some of it also reflects an increase in new construction. We turn to construction below.

Table A8

Estimates of value creation (broken out by corridor).

Value Add Under:	(Second)	(York)	(Lexington)
Treatment Effect	.085*** (0.012)	.038** (0.014)	-.006 (0.014)
Percentage Change	8.91	3.9	-.6
Owner-Occupied Residential (\$b)	31	19	54
Renter-Occupied Residential (\$b)	26	16	11
Commercial Non-residential (\$b)	12	23	16
Total (\$b):	69	57	81
Owner-Occupied Residential Created (\$b)	2.8	.73	-.33
Renter-Occupied Residential Created (\$b)	2.28	.61	-.07
Commercial Non-residential Created (\$b)	1.06	.88	-.1
Total Created (\$b)	6.13	2.22	-.49
Property Tax Receipts (\$b):	1.88	.68	-.15
Net Gain to Govt (\$b):	(2.62)	.68	-.15

A8. Value capture by corridors

As a robustness check on the value capture estimates, **Table A8** reports value capture results using the treatment estimates from **Table 4**. Because the treatment effect for the Second Ave corridor is estimated to be 8.5% in **Table 4** compared to 7.7% in our baseline **Table 3**, we obtain a capital gain of \$6.13 billion compared to \$5.53 billion in the main text. **Table A8** adds to that a capital gain of \$2.22 billion on York Ave, and subtracts a \$0.49 billion loss on Lexington Ave. The total value gained is \$7.86 billion, of which \$2.4 billion can be captured through property taxes. Of course, the cost of subway construction remains \$4.5 billion, so that the difference is now -\$2.1 billion. This net cost is similar to our baseline -\$2.8 billion estimate.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.jue.2021.103422](https://doi.org/10.1016/j.jue.2021.103422).

References

- Ahlfeldt, G.M., Redding, S.J., Sturm, D.M., Wolf, N., 2015. The economics of density: evidence from the berlin wall. *Econometrica* 83 (6), 2127–2189.
- Anderson, M., 2014. Subways, strikes, and slowdowns: the impacts of public transit on traffic congestion. *American Economic Review* 104 (9), 2763–2796.
- Andonov, A., Kräussl, R., Rauh, J., 2019. The Subsidy to Infrastructure as an Asset Class. Technical Report doi:[10.3386/w25045](https://doi.org/10.3386/w25045).
- Athey, S., Ferguson, B., Gentzkow, M., Schmidt, T., 2019. Experienced Segregation. Working Paper.
- Black, D.A., Kolesnikova, N., Taylor, L.J., 2014. Why do so few women work in new york (and so many in minneapolis)? labor supply of married women across u.s. cities. *J Urban Econ* 79, 59–71.
- Bom, P.R., Lighthart, J.E., 2014. What have we learned from three decades of research on the productivity of public capital? *J Econ Surv* 28 (5), 889–916.
- Bowes, D.R., Ihlanfeldt, K.R., 2001. Identifying the impacts of rail transit stations on residential property values. *J Urban Econ* 50 (1), 1–25.
- Cadot, O., Röller, L.-H., Stephan, A., 2006. Contribution to productivity or pork barrel? the two faces of infrastructure investment. *J Public Econ* 90 (6–7), 1133–1153.
- Calimente, J., 2012. Rail integrated communities in tokyo. *The Journal of Transport and Land Use* 5, 19–32.
- Campbell, J.Y., Shiller, R.J., 1988. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies* 1, 195–227.
- Campbell, J.Y., Shiller, R.J., 1989. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies* 1 (3), 195–228.
- Campbell, S., Davis, M., Gallin, J., Martin, R., 2006. What moves housing markets: a trend and Variance Decomposition of the rent-price ratio. Working Paper, Federal Reserve Board of Governors.
- Campbell, S.D., Davis, M.A., Gallin, J., Martin, R.F., 2009. What moves housing markets: a variance decomposition of the rent-price ratio. *J Urban Econ* 66 (2).
- Castells, A., Solé-Ollé, A., 2005. The regional allocation of infrastructure investment: the role of equity, efficiency and political factors. *Eur Econ Rev* 49 (5), 1165–1205.
- Cervero, R., Duncan, M., 2002. Transit's value-added effects: light and commuter rail services and commercial land values. *Transp Res Rec* 1805 (1), 8–15.
- Chen, M.K., Haggag, K., Pope, D.G., Rohla, R., 2019. Racial Disparities in Voting Wait Times: Evidence from Smartphone Data. Working Paper 26487. National Bureau of Economic Research doi:[10.3386/w26487](https://doi.org/10.3386/w26487).
- Chen, M.K., Rohla, R., 2018. The effect of partisanship and political advertising on close family ties. *Science* 360 (6392), 1020–1024. doi:[10.1126/science.aao1433](https://doi.org/10.1126/science.aao1433). URL <https://science.scienmag.org/content/360/6392/1020>.
- Cochrane, J., 2011. Discount rates. *Journal of Finance* 64 (4), 1047–1108.
- Couture, V., Duranton, G., Turner, M.A., 2018. Speed. *Review of Economics and Statistics* 100 (4), 725–739.
- Deweese, D.N., 1976. The effect of a subway on residential property values in toronto. *J Urban Econ* 3 (4), 357–369.
- Diao, M., Leonard, D., Sing, T.F., 2017. Spatial-difference-in-differences models for impact of new mass rapid transit line on private housing values. *Reg Sci Urban Econ* 67, 64–77.
- Fesselmeyer, E., Liu, H., 2018. How much do users value a network expansion? evidence from the public transit system in singapore. *Reg Sci Urban Econ* 71, 46–61.
- Finkenzeller, K., Dechant, T., Schäfers, W., 2010. Infrastructure: a new dimension of real estate? an asset allocation analysis. *Journal of Property Investment & Finance*.
- Haughwout, A.F., Inman, R., Craig, S., Luce, T., 2004. Local revenue hills: evidence and lessons from four U.S. cities. *Review of Economics and Statistics* 86, 570–585.
- Heblisch, S., Redding, S.J., Sturm, D.M., 2020. The making of the modern metropolis: evidence from london. *Q J Econ* 135 (4), 2059–2133.
- Hess, D.B., Almeida, T.M., 2007. Impact of proximity to light rail rapid transit on station-area property values in buffalo, new york. *Urban Studies* 44, 1041–1068.
- Jackson, C.K., Owens, E.G., 2011. One for the road: public transportation, alcohol consumption, and intoxicated driving. *J Public Econ* 95 (1), 106–121.
- Kahn, M., 2007. Gentrification trends in new transit oriented communities: evidence from fourteen cities. *Real Estate Economics* 35 (2), 155–182.
- Kahn, M.E., Baum-Snow, N., 2000. The effects of new public projects to expand urban rail transit. *J Public Econ* 77 (2), 241–263.
- Kahn, M.E., Baum-Snow, N., 2005. Effects of urban rail transit expansions: evidence from sixteen cities, 1970–2000. *Brookings-Wharton papers on urban affairs* 147–206.
- Koijen, R., Van Nieuwerburgh, S., 2011. Predictability of stock returns and cash flows. *Annual Review of Financial Economics* 3, 467–491.
- Lin, J.-J., Hwang, C.-H., 2004. Analysis of property prices before and after the opening of the taipei subway system. *Annals of Regional Science* 38 (4), 687–704.
- Lustig, H., Van Nieuwerburgh, S., Verdelhan, A., 2013. The wealth-consumption ratio. *Review of Asset Pricing Studies* 3 (1), 38–94. Review of Asset Pricing Studies.
- Lutz, B.F., 2008. The connection between house price appreciation and property tax revenues. *Natl Tax J* 61 (3), 555–572.
- McDonald, J.F., Osuji, C.I., 1995. The effect of anticipated transportation improvement on residential land values. *Reg Sci Urban Econ* 25 (3), 261–278.
- McMillen, D.P., McDonald, J., 2004. Reaction of house prices to a new rapid transit line: Chicago's midway line, 1983–1999. *Real Estate Economics* 32 (3), 463–486.
- Medda, F., 2012. Land value capture finance for transport accessibility: a review. *J Transp Geogr* 25, 154–161.
- Murakami, J., 2012. Transit value capture: New town codevelopment models and land market updates in Tokyo and Hong Kong. In: Ingram, G., Hong, Y. (Eds.), *Value Capture and Land Policies*. Lincoln Institute of Land Policy, Cambridge, MA, chapter 11.
- Nobbe, P., Berechman, J., 2013. The Politics of Large Infrastructure Investment Decision-Making: The Case of the Second Avenue Subway. Technical Report. University Transportation Research Center.
- Pan, H., Zhang, M., 2008. Rail transit impacts on land use: evidence from shanghai, china. *Transp Res Rec* 2048 (2048), 16–25.
- Petretta, D.L., 2020. The Political Economy of Value Capture: How the Financialization of Hudson Yards Created a Private Rail Line for the Rich. Columbia University Ph.D. thesis.
- Plazzi, A., Torous, W., Valkanov, R., 2010. Expected returns and the expected growth in rents of commercial real estate. *Review of Financial Studies* 23, 3469–3519.
- Ramey, V.A., 2020. The Macroeconomic Consequences of Infrastructure Investment. NBER Working Paper No. 27625.
- Severen, C., 2018. Commuting, labor, and housing market effects of mass transportation: welfare and identification. Working Paper (Federal Reserve Bank of Philadelphia).
- Stiglitz, J.E., 1977. The theory of local public goods. In: *The Economics of Public Services*. Springer, pp. 274–333.
- Van Nieuwerburgh, S., 2019. Why are reits currently so expensive? *Real Estate Economics* 47 (1), 18–65.
- Zheng, S., Kahn, M., 2013. Does government investment in local public goods spur gentrification? evidence from beijing. *Real Estate Economics* 41 (1), 1–28.
- Zhou, Z., Chen, H., Han, L., Zhang, A., 2020. The effects of a subway on house price: evidence from shanghai. *Real Estate Economics*. forthcoming.