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From announcement to operation: The changing impact of light rail transit on housing prices across implementation phases

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ABSTRACT

New public transit infrastructure can significantly influence housing prices. While most studies examine impacts only after construction or compare a limited number of implementation phases, little is known about how transit-induced property value capitalization evolves dynamically throughout the implementation process. This study investigates the impact of Montreal's new light rail project (the REM) on housing prices across four stages: announcement, construction, testing, and initial operation. The phased implementation of the REM also allows us to examine whether the operation of one branch generates anticipatory price effects along branches that remain under construction. Drawing on panel data of 14,711 residential property transactions over eleven years (from 2013 to 2023), we employ a natural experiment design through a difference-in-differences (DiD) approach to isolate the project's net effect at different stages on housing prices. Our findings show that the four stages of REM implementation affect property values differently across catchment areas along operating and non-operating branches. The project announcement raised housing premiums within 800 m of some parts of the corridor, and this effect persisted throughout the construction period. REM-related premiums around the branch that underwent testing remained positive throughout the construction period. However, during testing and early operation, these gains were largely offset, possibly due to operational impacts such as noise and vibration. While premiums dissipated near the operating branch, properties along unopened branches remained stable or continued to appreciate compared to the rest of the region. By highlighting how home values evolve across different stages of implementation of large-scale transit investments, this study provides insights that can inform the design of Land Value Capture policies to capitalize on property gains while mitigating externalities.

1. Introduction

The introduction of new public transit infrastructure has the potential of increasing residential property prices in its surrounding areas (Arku et al., 2024; He, 2020). These impacts on land values start taking effect upon the announcement of plans to invest in

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transport projects (Knaap et al., 2001). The construction period of such large projects can be disturbing and prolonged, leading to losses in the gains observed after the announcement (Chatman et al., 2011). While an extensive number of studies have examined the premiums brought by new transit infrastructure, most focus on post-operation outcomes once systems are in place (Debrezion et al., 2007; Hamidi et al., 2016; Rennert, 2022). Only a limited number of studies compared pre-to-post announcements home values (Chatman et al., 2011; Knaap et al., 2001), and only a few studies concentrated on comparing home values after announcement to after start of operation (Cengiz et al., 2022; Yen et al., 2018). However, these studies only focus on two implementation phases. As a result, little is known about how transit-induced capitalization evolves dynamically across phases of project implementation. To our knowledge, no study has tracked property value evolution continuously across all four phases (announcement, construction, testing, and operation) for multiple branches of a new public transit infrastructure system, allowing for both temporal and spatial comparison within a single natural experiment. Moreover, understanding how transit-induced capitalization evolves over time is not merely an academic gap. It is crucial for designing effective land use and transport policies, such as land value capture measures, that adapt to these temporal dynamics.

In Montreal, Canada, plans were announced in 2016 for the construction of the Réseau express métropolitain (REM), a new 67-km-long grade-separated light-rail (LRT) network, costing approximately CAD 9 billion (≈ USD 6.4 billion) (Réseau express métropolitain, 2021). The project was planned in three phases to connect different parts of the greater Montreal region. In 2018, the construction began, while the first phase of the project started operating in Summer 2023. This project provides a unique opportunity to study the impact of a transport project on housing prices. Beyond measuring changes in transit premiums from announcement through operation, the phased implementation allows us to examine whether the testing and operation of one branch generates spillover effects on property values along branches that remain under construction, reflecting anticipatory housing market responses to a gradually expanding transit network, a mechanism that has not been previously investigated.

Our study capitalizes on this opportunity by studying the impact of the REM on housing prices in the Montreal region during the four stages of the project: (1) announcement, (2) construction, (3) testing, and (4) operation of the first branch. We use repeated sales data from 14,711 transactions of residential properties over eleven years, from 2013 to 2023. The data was provided by Centris, a multiple listing service company operating in the province of Quebec. To isolate the effect of the REM on property prices, we employ a natural experiment design with a difference-in-differences (DiD) framework. DiD is a common approach that has been used in previous research to evaluate the impacts of infrastructure projects on home values (Gibbons and Machin, 2005; He, 2020; Im and Hong, 2018; Yen et al., 2018; Zhu and Diao, 2016). This study contributes to a deeper understanding of the impacts of large-scale transit investments on home values at different stages, which can help in capitalizing on the gains and mitigate the externalities that result from such investments.

2. Literature review

The impact of rapid transit on housing prices has been extensively studied in a variety of regional and local contexts. In a *meta*-analysis of 73 studies, Debrezion et al. (2007) examined how proximity to rapid transit stations (metro, light rail, commuter rail, and bus rapid transit) affects residential and commercial property values. They found that being within 400 m of a railway station increases residential property prices by an average of 4.2% compared to properties located farther away.

A later *meta*-analysis by Hamidi et al. (2016) covering 114 studies published from 1976 to 2014, found that the average single-family home (SFH) premium for being near public transit stations is only 2.3%. They attribute this lower estimate to several reasons. First, the newer studies focus on newer systems, which only provide limited increase in accessibility. Second, these studies controlled for other confounding variables in their statistical modeling such as neighborhood walkability. More recently, Rennert (2022) analyzed 66 rail access premiums, comparing properties located at 500 m to those located beyond 1.6 km from a rail station. They found that neighborhood demographics (e.g., racial and ethnic composition), data type (transaction vs. assessed sale prices), location of the study, planning policies (e.g., rent control policies), rail type (e.g., commuter rail, heavy rail, and light rail) influenced the magnitude of rail access premiums, ranging from − 7.4 to + 9.6 percentage points. Commuter and heavy rail generally yielded much higher premiums compared to light rail.

While such *meta*-analyses provide useful estimates of rail-based premiums under different conditions, most focus on the outcomes after rail systems are in place. Only a few studies consider the different phases of implementation. Cengiz et al. (2022) observed that the impact of the announcement of a metro line in Istanbul had a higher impact on housing sales prices than the operational phase. Similarly, Yen et al. (2018) showed that housing prices around light-rail transit (LRT) catchment areas in Gold Coast, Australia reached their highest increase after the announcement and financial commitments made by the government. From this point onwards, the prices increase at a lower rate during the construction and operation periods. Meanwhile, Pan (2019) argues that the significant impact of an LRT on housing prices after the start of operation is not instant.

While rail proximity is generally associated with increases in housing values, evidence shows that locations very close to the infrastructure can experience disamenity effects from noise, vibration, and construction-related disturbance. Chen et al. (1998) demonstrate that although accessibility gains from being near a light rail station are partly offset by nuisance effects, the net impact remains positive. Seo et al. (2014) identify an inverse U-shaped effect, with the highest LRT premiums for houses located around 800 m from stations, compared with lower premiums both closer in (400–800 m) and farther out. Similarly, Mulley et al. (2018) found that properties within 100 m of a station may suffer a loss in uplift, while those beyond that threshold increase in value the closer they are located from the station. These studies highlight that rail impacts reflect both accessibility benefits and local disamenities, stressing the importance of accounting for distance to transit infrastructure.

Beyond distance to stations, some studies specifically included variables to measure the impact of noise on housing values, further supporting the findings from the studies that found that close proximity has negative impacts on uplift in property values. In the Netherlands, Theebe (2004) found that noise from road, rail, and air traffic combined above a certain level (65 dB) has a statistically significant negative impact on property prices, while properties located in very quiet areas (below 40 dB) can sell for a higher premium. Using Swedish Data, Andersson et al. (2010) estimate that road noise has a larger impact on property prices than railway noise with both noise types being statistically significant. Similarly, a study in Hamburg, Germany by Brandt and Maennig (2011) found that both road and rail noise have statistically significant negative effects on condominium (condo) prices with road noise having a larger impact. Higher values of Soundscore, reflecting a lower level of noise, were associated with increases in housing values in California (Chernobai and Ma, 2022). These studies show that noise is a measurable disamenity that can offset accessibility benefits gained from LRT systems.

As land and property values increase due to transit investments, much of this value can accrue to landowners and developers while the costs of expanding the transit infrastructure is carried by the public sector. Land Value Capture (LVC) policies provide a means of ensuring that the value uplift generated by transit investment is shared with the government. Among the most commonly used LVC policies in the United States and Canada are Special Assessment Districts (SADs), Tax Increment Financing (TIF), betterment levies, development charges, density bonuses, and transit impact fees (Mathur, 2014; Siemiatycki et al., 2023). For example, two different LVC policies (dedicated 30-year property tax levy and one-time development charges) were implemented by the City of Toronto for funding different subway extensions (Siemiatycki et al., 2023).

In Richmond, British Columbia, a transit-oriented development (TOD) was planned around the future Capstan Station, and the associated density bonuses were collected and transferred to TransLink, the transport authority, to fund the design and construction of the station (Chan, 2024; TransLink, 2024). In this case, private funding was directly linked to the anticipated land value uplift generated by the transit infrastructure, illustrating a practical application of LVC to support TODs. These examples show the importance of leveraging land value uplift to help fund the construction and expansion of transit infrastructure.

Our study contributes to the international literature in three ways. First, while the broader literature on public transit and housing prices is extensive, most studies conceptualize transit implementation as a binary before-and-after event, overlooking how housing market responses evolve across transitional implementation phases. Our study tracks how transit-induced property value capitalization evolves across four phases of implementation: announcement, construction, testing, and operation. Second, by studying four branches of the same system simultaneously, we enable spatial comparisons that single-corridor studies cannot provide, isolating branch-specific effects while controlling for city-wide trends. Third, the phased implementation of the REM allows us to examine whether the testing and operation of one branch generates anticipatory price effects along branches still under construction, a spillover mechanism with direct relevance to how transit investments are sequenced and communicated to housing markets. The findings offer

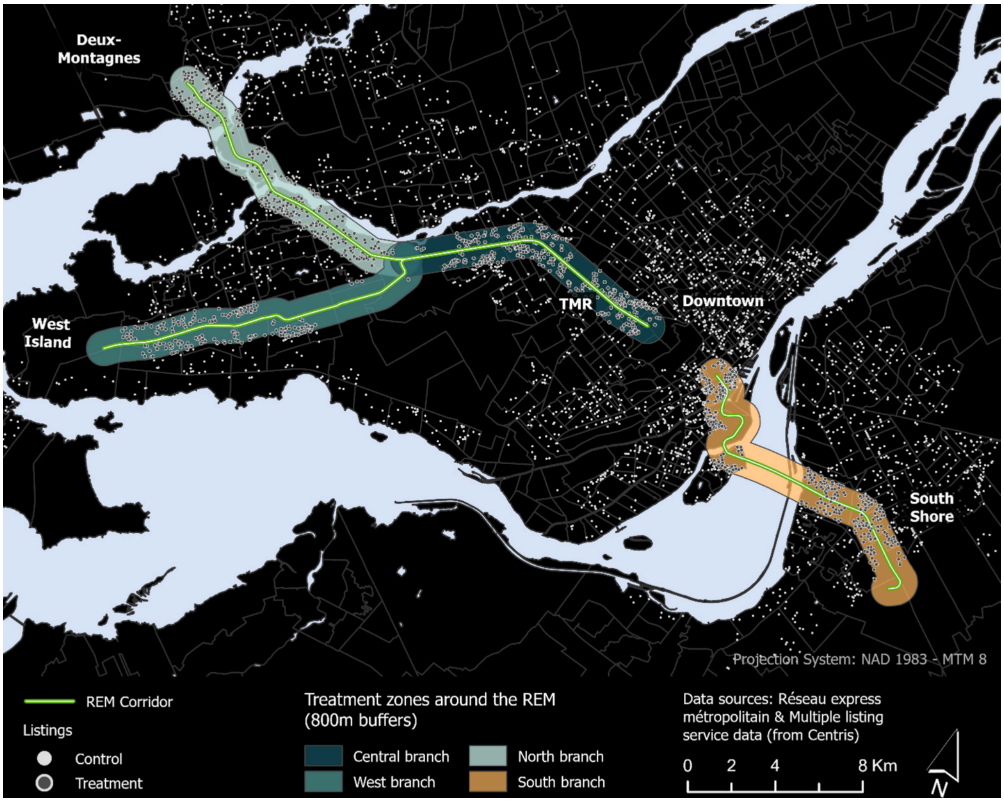

Fig. 1. Treatment zones around the REM and the properties locations in Montreal.

transferable insights for cities planning phased transit investments, particularly regarding how and when property value uplift materializes across a system's lifecycle, how phased implementation shapes market expectations, and how this timing can inform land value capture policy and transit infrastructure financing strategies.

3. Study context

The REM was announced in April 2016 as a 67-km-long grade-separated light rail network with 26 stations in Montreal, Quebec, Canada (Réseau express métropolitain, 2021). Fig. 1 shows the design of the network, which connects the South Shore of Montreal to its western (West Island) and north-western (Deux-Montagnes) areas via the Downtown core. The REM includes an airport branch, planned to open in 2027; however, due to the limited residential development in that area, this branch was excluded from our analysis. We also excluded the section from the REM that operates in a tunnel (Mount Royal Tunnel).

We define four branches of the REM as the South, Central, North, and West branches. These four branches differ considerably in their urban context and transit history, which motivates treating them separately. The Central and North branches follow the corridor previously served by the Deux-Montagnes commuter rail line, meaning the REM represents a service upgrade rather than entirely new infrastructure. Therefore, the REM does not introduce new noise or vibration to these surrounding neighborhoods. The Central branch runs through the consolidated urban fabric of the Town of Mont-Royal, while the North branch traverses a similarly consolidated but more suburban corridor toward Deux-Montagnes. By contrast, the West and South branches are built on entirely new alignments, with a considerable portion of each running along highway corridors. The West branch serves the less densely developed West Island suburbs, where land use near the corridor is particularly fragmented. The South branch connects the South Shore, an area of intermediate suburban density, to the downtown core via a new dedicated corridor. Construction began on all branches in April 2018. On the South Branch, dynamic testing started in early 2021, and operation began on July 31, 2023. In the time of the study, all other three branches were not in operation yet.

For each of the four branches, we define the catchment area (treatment zone) as 0–800 m from the REM corridor. Fixed-distance buffers are a widely used approach for defining treatment and control groups in studies examining the impacts of transport infrastructure (Spears et al., 2017; Sun and Du, 2023; Sun et al., 2020), including those on property values (Atkinson-Palombo, 2010; Diao et al., 2017; Mohammad et al., 2015; Spears et al., 2017). An 800 m buffer is often used in studies examining the impact of rail projects on housing prices (Dai et al., 2016; Devaux et al., 2017; Pan et al., 2014; Seo et al., 2014; Zhang and Shukla, 2022; Zhong and Li, 2016). In addition to these four groups, we define a control group as for properties within 801 to 8,000 m from the REM corridor. Fig. 1 illustrates these groups along with the distribution of properties within them.

4. Data

4.1. Multiple listing service data

We use residential property sales from the Montreal region, provided by Centris, a multiple listing service company operating in the province of Quebec. The dataset includes the location, property characteristics, sale date, and transaction price for 485,656 residential sales between 2013 and 2023. The property characteristics include the number of bedrooms above ground, bedrooms underground, bathrooms, washrooms, and a variable for the ‘total number of rooms.’ In Quebec, the total number of rooms includes the kitchen, living room, and bedrooms, with bathroom counted as 0.5 room. For example, a 3.5 property typically has a kitchen, living room, one bedroom, and a bathroom. Each property record contains information on lot and floor areas, building and unit types, and year of construction. For our analysis, we focus on repeated sales; properties that were sold more than once during this period. This focus allows for controlling for unobserved property characteristics, providing clear estimates of how external factors affect housing prices (Bailey et al., 1963; El-Geneidy et al., 2016; He, 2020). This subset includes 158,927 sales, corresponding to 74,627 unique properties.

The data cleaning process involved removing properties with unreasonable configurations such as larger number of bedrooms than total rooms, and number of total rooms higher than thirty. If the floor and lot area units (square foot [sq ft] or square meter [sq m]) were missing with no possibilities of imputation, the observations were dropped. Observations that were missing total number of rooms, year of construction, or both lot and floor areas were dropped. We removed outliers based on sale price, only retaining properties with a price range between CAD 150,000 to CAD 1,500,000. This cleaning process resulted in a sample of 116,492 transactions, out of which 37,329 were missing the floor area but had all the other property characteristics. The floor area for these observations was imputed using Multivariate Imputation by Chained Equations (MICE) via the R package mice (van Buuren and Groothuis-Oudshoorn, 2011). The imputation process incorporated variables such as lot area, total number of rooms, building type, and unit type.

As described in Section 3, we categorize properties based on falling into one of the four treatment areas (South, Central, North, West branches) or the control group. The control group is limited to dwellings within 8,000 m of the REM corridor to ensure that treated and control properties remain within a comparable urban context and are subject to similar regional market conditions. Further, to ensure comparability between treatment and control properties, we apply propensity score matching (PSM), which reduces selection bias by ensuring that treated and control properties share similar observable characteristics. We estimate propensity scores using a logit model with six covariates: floor area, lot area, building age, single-family dwelling type, Walk Score, and accessibility by public transit. We then apply 1:1 nearest-neighbour matching, retaining only matched treatment–control address pairs.

The final sample comprises of 14,711 sales corresponding to 6,948 unique properties. Most of these properties (N = 6,189) were sold twice within the study period, with others sold up to five times.

4.2. Accessibility data

Accounting for changes in accessibility, defined as the number of opportunities reachable within a certain travel time by different modes (El-Geneidy and Levinson, 2022), is crucial in hedonic models as it reflects a relevant component of the spatial benefits of infrastructure investments (Higgins and Kanaroglou, 2016). In our study, we include both local and regional accessibility measures. Local accessibility was accounted for using Walk Score®, a gravity-based indicator that uses a decay function to evaluate access to various amenities (dining and drink, groceries, parks, schools, shopping, culture and entertainment, and errands) within a 30-minutes walk of a certain location (Walk Score, 2024). The score is continuous, and ranges from 0 (car dependent) to 100 (walker's paradise). Walk Score® is a reliable walkability index that has been extensively used in previous studies that examined and confirmed the positive impact of walkability on residential property values (Chernobai and Ma, 2022; Gilderbloom et al., 2015; Pivo and Fisher, 2011; Xu et al., 2018). As historical Walk Score® cannot be retrieved, we relied on three archived datasets from 2013, 2019, and 2024, where Walk Score® for each postal code was retrieved using an Application Programming Interface (API). Each property listing was matched to the nearest available dataset by postal code according to its year of sale: listings sold in 2013–2015 were linked to the 2013 dataset, those sold in 2016–2020 to the 2019 dataset, and those sold in 2021–2023 to the 2024 dataset.

The impact of regional accessibility by public transit has been the focus of many studies examining its impact on housing prices for different neighborhoods (Arku et al., 2024; He, 2020; Seo et al., 2014). We account for regional accessibility using cumulative opportunities measure of accessibility calculated for each year of study at the census tract (CT) level. Including this measure when modelling property values takes into account the year-to-year changes in regional transit accessibility resulting from changes across all public transit modes. Three data sources are required to calculate this measure: the number of jobs per CT, General Transit Feed Specification (GTFS) data, and OpenStreetMap networks. The 2016 Canadian population census and commuting flows (CCF) (Statistics Canada, 2017) is used to identify the number of jobs present in each census tract (CT) in the Montreal metropolitan region. The number of jobs in an area is used in the accessibility literature as a proxy for the quantity and diversity of services and products that the area offers (El-Geneidy and Levinson, 2022); thus, representing the different opportunities that individuals seek to reach. We opted for consistency with the use of 2016 data to focus on changes in the transport system in Montreal when comparing accessibility across the different years.

GTFS data was obtained from Transitland using an API for each year to match the sales date and represent the yearly state of the public transit system. The OpenStreetMap street network was obtained for the Montreal Census Metropolitan Region (CMA) through BBBike extracts. We used the r5r package in R with GTFS data and the OSM network for the Montreal CMA as inputs to calculate the travel time matrix between CT centroids (Pereira et al., 2021) for a regular Wednesday travelling at any minute between 8 AM and 9 AM. The median value is then used to account for schedule variability. The calculated travel time includes access, egress, waiting, in-vehicle, and transfer times if applicable. To calculate the cumulative opportunities measure, the travel-time threshold was set to 45 min as it is closest to the median travel time by public transit in Montreal (Statistics Canada, 2023) as suggested by Kapatsila et al. (2023). To be able to accurately capture accessibility gains and losses, we use proportional accessibility by dividing the accessibility value by the total number of jobs in the region. The accessibility data was connected to each property based on its CT.

5. Methods

To provide an overview of how the different stages of the REM influenced housing prices, we first conduct an exploratory analysis of changes in average selling prices within 800 m of each branch between 2013 and 2023. We then analyze these impacts in greater depth using hedonic multilevel log-linear regressions that control for property characteristics, local and regional accessibility, year of sale, and catchment areas. A log-linear regression is one in which the dependent variable (transaction price in this case) is log-transformed while independent variables are kept in their original scale. This is a common specification in hedonic pricing studies (Arku et al., 2024; Chernobai and Ma, 2022; He, 2020). The log transformation addresses the right-skewed distribution typical of housing prices and reduces heteroscedasticity. Crucially, it allows regression coefficients to be interpreted as approximate percentage changes in price, making results more intuitive and directly comparable across studies.

Four models are estimated sequentially, with each building on the previous one. The gradual buildup of modelling frameworks progresses from a basic model (Model 1), which captures general property value trends across the 11-year period, to a natural experiment design (Model 4), which isolates the effects of the REM's announcement, construction, testing, and introduction. This stepwise design provides insights into the relevance of introducing different sets of variables within the analysis of property values.

Model 1, the base model, represents the most basic iteration of the hedonics model. This model includes property characteristics and yearly fixed effects, which account for aggregated temporal trends. These yearly fixed effects are key to understanding the underlying temporal trends affecting the housing market over the 11 years of analysis such as the impacts of the COVID-19 pandemic. Model 2 incorporates local and regional accessibility measures, in addition to all variables included in model 1.

Model 3 includes spatial fixed effects variables to represent four treatment groups around the REM. For each of the four branches of the project, spatial buffers are defined by airline distance to the project. This model provides insight into the differences in property values between areas around the REM compared to the rest of the region.

Model 4 uses a natural experiment approach to isolate the impacts of the different stages of the project on property values. This design implies the definition of a before-and-after, treatment/control framework, which can isolate the impacts of the REM. Model 4 includes additional interaction variables between yearly fixed effects and spatial treatment groups. These interactions represent treatment effects which isolate the impact of the REM on home values at different points in time. Model 4 represents the DiD framework, which is most simply defined as follows (Craig et al., 2017):

$$Y_{it} = \beta_0 + \beta_1 exposure_i + \beta_2 time_t + \beta_3 exposure_i \times time_t + \beta_4 X_i \tag{1}$$

Here, Y_{it} is the outcome for observation i at time t. The variable $exposure_i$ is most simply coded as 1 for observations in the treatment group and 0 for those in the control group. Thus, the coefficient β_1 controls for spatial differences at baseline, also called observed effects. That is because this coefficient represents the difference in the outcome between treatment and observation groups before the intervention. The binary dummy variable $time_t$, is most usually simply coded as 0 for pre-intervention times, and 1 for post-intervention. Thus, the coefficient β_2 controls for temporal trends, also named unobserved effects. This represents the average change in the outcome post-intervention regardless of exposure. Finally, the coefficient β_3 is the treatment effect, as it measures the change in the outcome for exposed observations post-intervention. In this sense, the treatment effect β_3 is the most relevant result in this type of model, as it isolates the impact of the intervention from spatial and temporal biases. The variable X_i represents a confounding effect.

For simplicity, Equation (1) presents one treatment measured at only one point in time and one confounding variable. In this study, however, the framework is extended to account for eleven years of observations (2013–2023) and four treatment groups (South, Central, North, and West branches), in addition to the control group. The year 2013 serves as the base year, and the control group serves as the reference category, such that all treatment effects are interpreted relative to unaffected properties in the pre-announcement period.

The validity of this framework rests on the parallel trends assumption. That is, the assumption that treatment and control properties would have followed the same price trajectory in the absence of the REM. We test this directly using the pre-announcement period (2013–2015), during which no intervention had yet occurred. The absence of statistically significant treatment effects in these years supports the parallel trends assumption and rules out pre-existing divergences between groups. Anticipation effects are also of interest in this framework, as housing markets may begin responding to a project before it is formally underway. This is precisely what we address by tracking treatment effects from the announcement year (2016) onward, allowing us to capture any market response that emerged as soon as the REM became public knowledge.

All models in this study are estimated using multilevel log-linear regressions. In this framework, the higher level of the random-effect structure (property level) accounts for the longitudinal component of the dataset. The statistical framework recognizes that there are repeated observations of the same property over time. All regressions were estimated using the lme4 R package (Bates et al., 2015).

6. Results

6.1. Descriptive statistics

Table 1 presents the descriptive statistics (mean and standard deviation) for the variables included in our analysis of residential properties, categorized into five groups: the control group and four groups for properties within 800 m from each REM branch. Properties in the four treatment areas are of similar average price, which is slightly more expensive than the control group. On average, West and North branches properties are larger, with more rooms, and greater floor and lot areas. Almost 70% of these properties are single-family homes (SFH), compared to only about 20% and 30% along the South and Central branches, respectively. Meanwhile, the South and Central branches properties have better local and regional accessibility with higher Walk Score® and proportional accessibility by public transit values. Table 2 reports the number of transactions per year for each group. A marked increase in sales across all groups is observed during the 2019–2021 period, driven by lower mortgage interest rates and relocations related to COVID-19 (QPAREB, 2021, 2022a).

Table 1
Mean (SD) of the sample variables by treatment and control groups.

	Control group	South branch	North branch	Central branch	West branch
Observations (N)	7,380	3,645	1,259	1,812	615
Unique properties (N)	3,474	1,733	599	852	290
Price (x 10,000 CAD)	33.6 (17.3)	42.6 (18.3)	45.0 (21.8)	42.2 (23.0)	41.4 (25.0)
Bedrooms above ground (number)	2.2 (0.9)	1.9 (0.8)	2.5 (0.9)	2.4 (0.9)	3.0 (0.9)
Bedrooms underground (number)	0.4 (0.7)	0.2 (0.5)	0.5 (0.7)	0.2 (0.5)	0.5 (0.6)
Additional bathrooms (number)	0.3 (0.6)	0.3 (0.5)	0.4 (0.5)	0.5 (0.6)	0.8 (0.7)
Washrooms (number)	0.3 (0.5)	0.2 (0.4)	0.3 (0.5)	0.3 (0.5)	0.7 (0.6)
Total number of rooms	7.1 (2.5)	6.0 (2.3)	8.4 (2.3)	7.1 (2.4)	9.1 (2.7)
Floor area (m^2)	102 (40)	89 (36)	107 (32)	112 (48)	139 (60)
Lot area (m^2)	249 (255)	153 (185)	435 (302)	228 (235)	450 (256)
Building age	40 (31)	35 (37)	47 (22)	43 (29)	38 (19)
Single family home (SFH) [Yes = 1]	0.3 (0.5)	0.2 (0.4)	0.7 (0.5)	0.3 (0.5)	0.7 (0.4)
Year of transaction	2018 (3.0)	2019 (3.0)	2018 (3.1)	2018 (3.0)	2018 (3.0)
Walk Score®	71 (24)	81 (20)	48 (16)	71 (16)	51 (17)
Accessibility by PT in 45 mins (% of jobs accessible in year of transaction)	17 (16)	25 (13)	1 (1)	18 (11)	2 (1)

6.2. Exploratory analysis

Before estimating the hedonic model, Fig. 2 shows the evolution of average selling prices for properties located within 800 m of the REM along the South branch where testing began in 2021 and operation in 2023, the North/Central/West branches (not in operation yet), and the control group. Between 2013 and 2016, home values rose by an average of 2.8% in the control group, 3.7% along the North/Central/West branches, and 0.5% along the South Branch per year. A pronounced increase occurred in 2017, following the announcement of the REM: prices rose by 9.5% and 5.5% along the North/Central/West branches and South branch, respectively, while the control group experienced a 7.2% increase. This pattern highlights the capitalization of anticipated transit investment into housing values prior to construction.

Beginning in 2020, the housing market experienced unprecedented growth driven by the impacts of the COVID-19 pandemic. That year, property prices increased by 8.5% in control areas, 14% along the North/Central/West branches, and 10.4% along the South Branch. However, the surge in mortgage rates in 2023 reversed this trend. Prices fell by 5.9% in control zones and by 0.8% along the North/Central/West branches; while prices increased by a mere 0.1% around the newly operational South branch.

Opposite to the overall decrease in home values in the control group and around the non-operating branches, the slight increase in prices around the South branch are recorded despite the residents' complaints regarding noise and vibrations associated with REM testing and operations (CityNews, 2023; Réseau express métropolitain, 2023) and the changes in bus service along the operating REM line, which faced backlash from local residents (Ouellette-Vézina, 2023; Société de transport de Montréal, 2023). This suggests that the accessibility benefits associated with the project may have outweighed these negative externalities in the housing market. To further examine and isolate the impact of the REM on these housing price trends, we conduct statistical analyses using a DiD framework in the subsequent section.

6.3. Hedonic models

Four models predicting the log-transformation of property values in Canadian Dollars ($CAD) were estimated. These four models represent a gradual buildup from a base hedonics model (Model 1) towards a natural experiment design (Model 4). The results of the four sequential models are presented in Table 3. Since all models are estimated with a multilevel structure, results include both fixed effects, representing the marginal impact of explanatory variables on home values, and random effects, which account for the fact that multiple sales are reported for the same property.

6.3.1. Base model

The base model represents the most basic iteration of property-value prediction. The explanatory factors in this model include dwelling and lot characteristics, as well as yearly fixed effects, which account for aggregated temporal trends in home prices. All dwelling and lot characteristics have statistically significant effects on property values. Most of these effects confirm expected results, such as the addition of rooms above ground (+6.4%) or underground (+3.0%), additional bathrooms (+28.6%), washrooms (+10.7%), or total number of rooms (+0.3% per room) all increasing property values, all else kept at mean value. Similarly, as expected, larger floor areas increase home values (+0.3% per m^2), holding other attributes at their mean levels. The effect of building age is as expected in the model and is captured through the regular and square terms. The squared term for building age is statistically significant and indicate a U-shaped relationship, showing that buildings aged 37 years have the lowest value, ceteris paribus. Buildings younger or older than 35 years would both have higher values, with remaining factors held constant.

However, certain unexpected results can be seen for this model, such as SFH being 6.4% cheaper than other types of dwelling and increasing lot area decreasing the price by 0.003% per m^2, when keeping all else constant. These results can be attributed to an omission of key variables in this base model, as it will be shown in the results of following models.

Yearly fixed effects in this model control for aggregated temporal trends in home values within the Montreal region. All coefficients are positive and generally increasing over time, representing an overall increase of home values from year to year, with other variables fixed at their mean. The only exception is a slight reduction in overall property values between 2022 and 2023, consistent with results

Table 2
Number of transactions for each year and treatment group.

	Control group	South branch	North branch	Central branch	West branch
2013	597	255	128	148	44
2014	557	200	97	135	65
2015	591	239	103	145	53
2016	574	270	99	148	58
2017	710	357	118	173	65
2018	706	411	110	178	64
2019	767	399	140	203	64
2020	818	382	128	214	59
2021	835	484	137	203	63
2022	656	334	107	136	44
2023	569	314	92	129	36
Total transactions	7,380	3,645	1,259	1,812	615

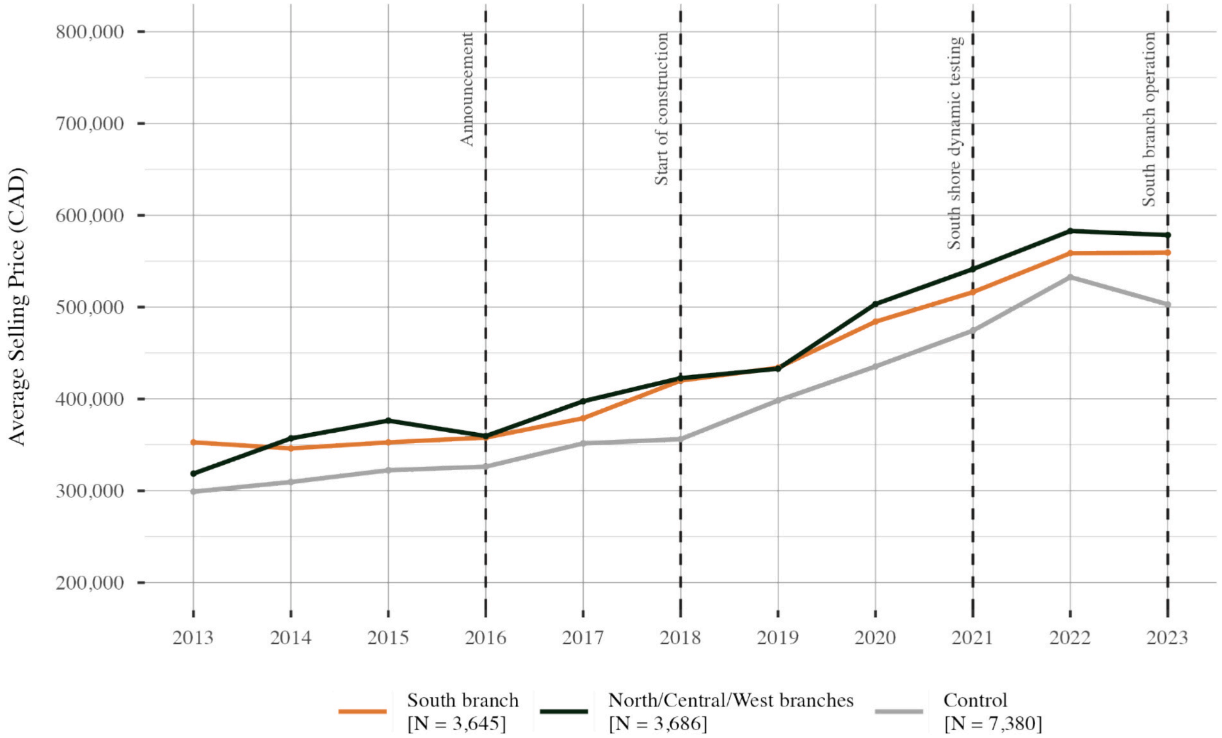

Fig. 2. Properties sales prices in relation to the REM phases within 1600 m of the West (planned) and South (operating as of 2023) branches.

shown in Fig. 2. As expected, a particularly large increase in home values was seen between the years 2020 and 2022, due to the pandemic.

6.3.2. Accessibility model

The second model of home-value prediction incorporates two accessibility metrics in addition to all variables in Model 1. The inclusion of these metrics presents expected results, where an additional point of Walk Score® represents a home-value increase of 0.1%, holding all else constant. Similarly, an increase of one percentage point in accessibility by public transit represents an increase of 1.2% in property value, with other characteristics fixed at their mean values.

Most importantly, the inclusion of these accessibility metrics resolves all unintuitive results seen in Model 1. When considering the effect of local and regional accessibility, there is a positive effect of lot area (+0.01% per m^2), controlling for other factors at their mean. Similarly, the price of a SFH is now unraveled as 4.4% more than other types of property, ceteris paribus. Additionally, while the unexpected results in Model 1 are resolved, all previously expected results are largely maintained.

The inclusion of local and regional accessibility metrics considerably increases the model goodness of fit, as reflected in a reduction in AIC and BIC values compared to Model 1, as well as a considerable increase in the Marginal R^2 values. Whereas Model 1 explained 54.2% of the variance in home values, adding accessibility measures in Model 2 explained 66.8% of the variance.

6.3.3. Spatial REM model

In addition to all Model 2 variables, Model 3 includes spatial fixed effects of the four treatment groups considered for their proximity to the four REM branches. The treatment groups were modelled as dummy variables.

The spatial dummy variables for the South, Central, and West branches have positive and statistically significant values. This indicates that these areas within 800 m from the REM project had higher property values at baseline (2013) compared to properties located within 801–8,000 m from the REM. Homes located within the buffers surrounding the South, Central, and West branch had higher property values of 11.1%, 13.2%, and 13.1% compared to the rest of the region, respectively, ceteris paribus. Meanwhile, properties located within 800 m of the North branch had lower property values at baseline (5.9% less than the control group), all else other variables kept at their mean values.

Including these spatial dummies does not result in any relevant change to the fixed effects compared to Model 2. However, this model does not yet explicitly address the measurement of the impacts of the REM on property values over time, which is included in the following model.

6.3.4. REM natural experiment

Model 4 presents the full natural experiment design around the introduction of the REM project. This is achieved by including the

Table 3
Sequential modeling of residential properties values (log of $CAD).

	Model 1		Model 2		Model 3		Model 4	
	Base		Accessibility		Spatial REM		REM Natural Experiment	
Intercept	12.1898	***	11.7332	***	11.7016	***	11.713	***
Dwelling and lot characteristics								
Bedrooms above ground	0.0625	***	0.0843	***	0.0832	***	0.0833	***
Bedrooms underground	0.0294	***	0.0354	***	0.0385	***	0.0382	***
Additional bathroom	0.2514	***	0.2307	***	0.2178	***	0.218	***
Washroom	0.1017	***	0.1001	***	0.0929	***	0.0939	***
Total N of rooms	0.0029	*	0.0079	***	0.0088	***	0.0088	***
Floor area (m^2)	0.0028	***	0.0031	***	0.0031	***	0.0031	***
Lot area (m^2)	−0.00003	*	0.0001	***	0.0001	***	0.0001	***
Building age	−0.0074	***	−0.0057	***	−0.0054	***	−0.0054	***
Building age squared	0.0001	***	0.00004	***	0.00004	***	0.00004	***
SFH [Yes = 1]	−0.0661	***	0.0428	***	0.0487	***	0.0473	***
Yearly fixed effects								
2014	0.006		0.0065		0.006		0.0006	
2015	0.022	**	0.0192	**	0.0195	**	0.0161	
2016	0.0309	***	0.0289	***	0.0283	***	0.018	
2017	0.0942	***	0.0927	***	0.0925	***	0.0825	***
2018	0.1635	***	0.1716	***	0.1702	***	0.1478	***
2019	0.2367	***	0.2449	***	0.2444	***	0.2304	***
2020	0.3571	***	0.3695	***	0.3686	***	0.3518	***
2021	0.4754	***	0.482	***	0.482	***	0.4863	***
2022	0.5731	***	0.5877	***	0.5883	***	0.594	***
2023	0.5446	***	0.5595	***	0.5595	***	0.5647	***
Accessibility metrics								
Walk Score®			0.0007	***	0.0005	**	0.0005	**
Accessibility by Public Transit (%)			0.0121	***	0.0117	***	0.0116	***
REM spatial groups								
South branch (0–800 m)					0.1052	***	0.0883	***
Central branch (0–800 m)					0.1236	***	0.1299	
North branch (0–800 m)					−0.0612	***	−0.0763	**
West branch (0–800 m)					0.1234	***	0.0588	*
Treatment Effects							**Omitted for brevity, see Fig. 3**	
Random effects								
ICC	0.82		0.75		0.74		0.74	
N (unique properties)	6948		6948		6948		6948	
Observations	14,711		14,711		14,711		14,711	
AIC	−1150.6		−3524.3		−3903.1		−3889.6	
BIC	−975.8		−3334.4		−3682.8		−3365.4	
Marginal R2 / Conditional R2	0.542 / 0.919		0.668 / 0.917		0.687 / 0.918		0.688 / 0.920	

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$.

treatment effects of the REM on each of the six spatial groups over each of the study years. These treatment effects correspond to interaction terms between the ten yearly fixed-effect dummies (2014 to 2023) and the four spatial groups included in Model 3. Fig. 3 presents the treatment effects coefficients from the announcement of the REM until its start of operation in the South branch.

Notably, the treatment effects in the pre-announcement years (2013–2015) are not statistically significant across all branches, strongly supporting the parallel trends assumption underlying the DiD framework. This indicates that, prior to the REM announcement, property values in the treatment areas were evolving in line with the control group, lending credibility to the causal interpretation of the subsequent estimates.

From the announcement until the start of construction in 2018, the REM caused an increase in property values within 800 m of the South and West branches at varying rates. By the start of construction (2018), the REM induced gains of up to 10.2% in the West branch properties and 7.2% in the South branch properties, relative to the control group, holding all other variables constant. By 2021, when dynamic testing on the South branch started, REM premiums reached a peak in the West branch (+13.4%), while the premiums around the South branch were reversed, with properties beginning to underperform the control group relative to 2013.

Leading up to and by the start of operation of the South Branch in 2023, the previously accumulated premiums in the South branch dissipated, with properties around that branch underperforming the control group relative to 2013 (−4.49%). Meanwhile, the premiums around the West branch remained positive but declined to 8.5% above the control group, relative to the 2013 baseline.

According to our model, the REM did not have any statistically significant impact on the properties around the Central branch. On the other hand, the dwellings within 800 m of the North branch only witnessed statistically significant premiums in the last two years, reaching 9.4% in 2023, relative to the control group in 2013.

7. Discussion

Over the last decade, the housing market in Montreal has witnessed significant changes, driven by the COVID-19 pandemic and

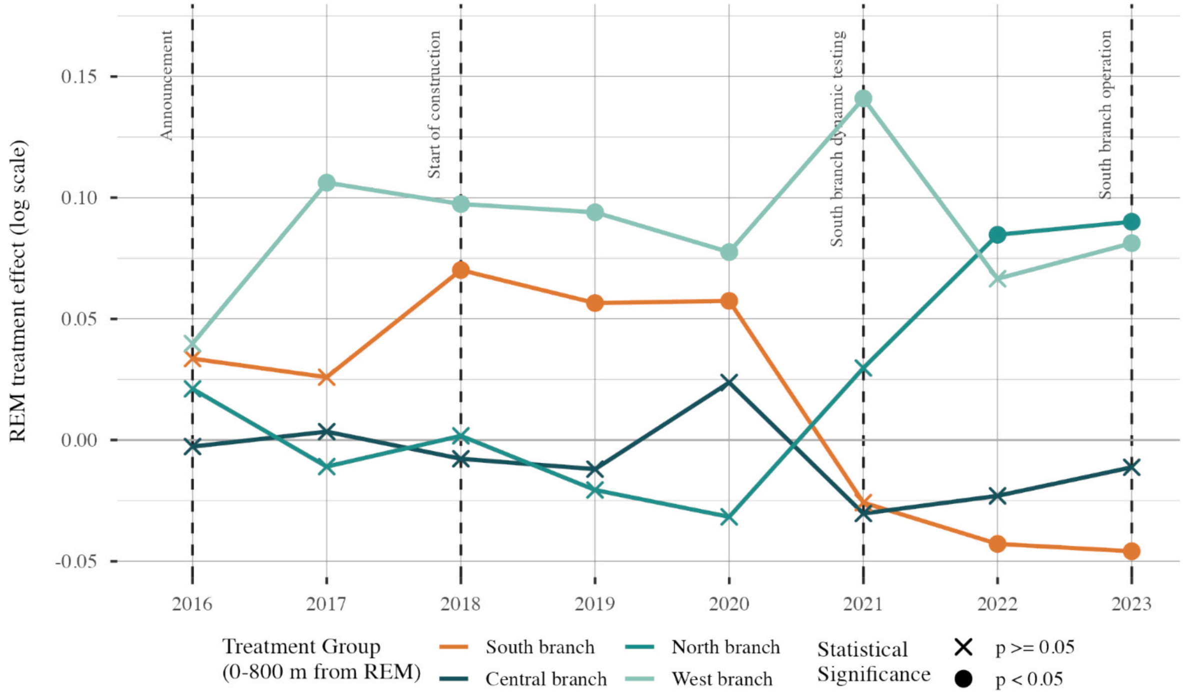

Fig. 3. Treatment effects of the REM on residential properties values.

fluctuations in mortgage interest rates. In the years preceding the pandemic (2017–2019), SFH and condo values rose by 4–7% annually on average (QPAREB, 2018, 2019, 2020). Our findings from the base model (Model 1), which does not incorporate controls for the impact of the REM, align with this pattern, as the yearly fixed effects show increases in property values of 7.1% each year on average in the three years.

The pandemic, combined with historically low interest rates, accelerated the growth in housing prices. In 2020, SFH values rose by 22% and condos by 12%, followed in 2021 by further gains of 20% and 17%, respectively (QPAREB, 2021, 2022a). Our base model results match this surge, showing a 12.8% increase in 2020 and a further 12.6% rise in 2021.

While prices continued to grow in 2022, though at a slower rate (QPAREB, 2022b), the rise in interest rates by the end of the year triggered a decline (QPAREB, 2023b). This decline was mostly witnessed in the first half of 2023 with SFH losing up to 6% of their values (QPAREB, 2023a). According to our base model, prices rose by 10.3% in 2022 then fell by 2.8% in 2023. Given that our model pools property types rather than disaggregating by SFH and condo, exact figures are not directly comparable to QPAREB's reported trends, though both capture the same overall pattern of sharp pandemic-era growth followed by post-pandemic adjustment.

The alignment of our base hedonic model findings with overall market trends in Montreal demonstrates the reliability of the data and supports the rigor of the subsequent natural experiment–based model. The effect of the control variables introduced in the natural experiment model are consistent with previous research on the impact of property characteristics, as well as local (Chernobai and Ma, 2022; Xu et al., 2018) and regional accessibility (Arku et al., 2024; He, 2020) on housing prices. The changes in coefficients from Model 2 to Model 3 suggest that, when accessibility metrics are not explicitly accounted for, their effect may be absorbed by property characteristics more related to urban sprawl and peripheral locations. Controlling for such variables is essential to accurately isolate the impact of the REM on housing prices, as shown by previous research (El-Geneidy et al., 2016).

Our DiD framework indicates that the different stages of REM implementation (announcement, construction, testing, and operation) affect housing prices to varying degrees in catchment areas along both the operating and non-operating branches. The announcement of the REM in 2016, REM-related premiums amounted to a 1.8–2.4% increase in average property prices within 800 m of the West and South branches. Such announcement-induced premiums have been previously observed in the context of large transport projects (Cengiz et al., 2022; Yen et al., 2018).

In 2020, nearing the end of construction on the South branch, REM-related premiums remained positive around that branch at 5.9% and 8.1% around the West branch, relative to the control group in 2013. The REM testing on the South branch in 2021 and 2022 sparked noise complaints from residents along that corridor (Sargeant, 2023). These disamenities nullified the REM-related premiums gained near that branch, dropping them in 2022 to −4.2% (relative to the control group in 2013). The negative perception spilled over to the West branch (still under construction), though REM-related premiums there remained relatively high, at 6.8%, though statistically insignificant.

Operation of the South branch began in 2023. That year, premiums around the operating branch declined further, to the point of negatively influencing the average housing prices within the close to middle range which typically has been noted to benefit from transport projects in previous research (Mulley et al., 2018; Seo et al., 2014). Meanwhile, properties along the West branch restored premiums of 8.5%, relative to the control group in 2013.

The drop along the South branch may reflect noise and vibration disamenities outweighing the project's gains, especially with major bus service adjustments affecting South Shore-downtown connections (Réseau de transport de Longueuil, 2023). In contrast, the West branch retained premiums likely due to speculation about accessibility benefits and fewer noise concerns, since testing had not begun.

In response to complaints, REM developers have revisited noise mitigation strategies (Réseau express métropolitain, 2023, 2024). Measures such as dynamic absorbers and acoustic maintenance are under consideration and could yield positive results. Previous research shows that the announcement and installation of sound barriers can both boost housing prices (Lee and Pang, 2022; Thiel, 2024).

The North branch corridor shows a unique pattern. Properties along this corridor begin appreciating around 2022–2023, coinciding with the testing and early operation phases of the South branch. This is notable given that the Deux-Montagnes commuter rail line, which had previously served the North branch corridor, was permanently closed in 2021 to facilitate REM construction. Rather than depressing nearby property values, the closure coincided with growing premiums, suggesting that the South branch's testing reinforced market confidence in the broader REM network's delivery. This reflects a spillover of anticipatory effects across branches where observable progress on one corridor appears to have updated buyer and investor expectations about the timeline of adjacent, still-incomplete segments.

Our findings contribute to and extend the international literature on transit-induced property value capitalization in several ways. The anticipatory premiums observed following the REM announcement and start of construction are consistent with evidence from Istanbul (Cengiz et al., 2022) and Gold Coast (Yen et al., 2018), confirming that housing markets in different national contexts respond to credible transit commitments. This suggests that announcement effects are not context-specific but reflect a generalizable market mechanism whereby investors and homebuyers price in expected accessibility gains ahead of delivery.

The disamenity effects observed during testing and early operation, manifesting as a reversal of premiums near the operating branch, align with findings from the Netherlands (Theebe, 2004), Germany (Brandt and Maennig, 2011), and Sweden (Andersson et al., 2010) where noise and vibration from rail infrastructure were shown to negatively affect property values in close proximity. Our results suggest that these disamenity effects are not limited to mature systems but can emerge rapidly during the transition from construction to operation and may temporarily dominate accessibility benefits in the short run. This has not been explicitly demonstrated across multiple branches of the same system in prior international research.

Our study highlights how the REM has the potential to generate measurable increases in property values in its vicinity. Policymakers could harness these uplifts through Land Value Capture (LVC) policies such as development charges, density bonuses, or betterment levies. The dynamic variation in premiums across stages and locations suggest that timing and spatial targeting are critical for maximizing the effectiveness of LVC strategies. For example, higher premiums in zones within 800 m of the project indicate areas where LVC interventions could generate great returns. The current blanket development tax policy around the REM might not be capturing all value uplift due to its limitation in space and time (Siemiatycki et al., 2023).

These findings are particularly relevant as cities worldwide continue to invest in large-scale transit infrastructure. As phased transit expansion becomes increasingly common in growing metropolitan areas, the lessons drawn from the REM experience offer a transferable framework for anticipating where and when value uplift is likely to occur, enabling more strategic and timely deployment of LVC mechanisms in future projects.

8. Conclusion

This study investigates the impacts of a new light rail project (the REM) on housing prices in Montreal across four stages: announcement, construction, testing, and operation of the first branch. Using data from 14,711 residential property transactions over eleven years, we apply a DiD approach to isolate the project's net effect on property values. We find that the announcement of the project increased housing premiums within 800 m of some parts of the corridor, and this effect persisted despite construction-related disruptions. However, results show that testing and operation stages may largely offset these gains due to disamenities such as noise and vibration. The impact of the project at these stages may even become negative if not compensated by substantial accessibility improvements and travel time savings. Despite the nullification of REM-related premiums near the operating branch, properties around branches not yet in service can continue to appreciate. Even where existing rail service is replaced and temporarily discontinued during construction, housing markets may still respond positively once the broader system begins reaching advanced stages of delivery on other branches.

Beyond the Montreal context, this study offers several transferable lessons for cities planning or delivering large-scale transit investments. The finding that announcement effects are real and measurable suggests that transparent and credible project communication can generate housing market responses before and during construction, with implications for the timing of Land Value Capture (LVC) policy activation. The rapid reversal of premiums upon the onset of operations underscores the importance of proactive noise mitigation strategies during the transition to service, a lesson relevant to any urban rail project. Finally, the multi-branch natural experiment design employed here offers a methodological template for future studies in cities where transit systems are being expanded in phases, enabling spatial and temporal comparisons that single-corridor studies cannot provide. This was particularly useful in disentangling how replacing a legacy rail line with the new system can yield premiums even before the replacement service enters operation.

Due to the recent operation of the REM, our study is limited by the availability of the data up to the start year of operation, making it impossible to evaluate the project's evolving effects after inauguration. As Pan (2019) highlights the lasting impact of a new transit system becomes more evident after a few years of operation. Future research can examine this evolving impact, further analyzing long-term changes in property values, neighbourhood development, travel behaviour, and social or demographic shifts within catchment areas. As the developer of the REM project started implementing noise mitigation strategies along the corridor recently, the impacts of these strategies can be a focus of future studies. Additionally, while the 800-meter buffer was selected based on literature support and sensitivity testing, future studies could employ data-driven approaches, such as local polynomial regression (Linden and Rockoff, 2008), to identify optimal treatment boundaries, potentially refining the spatial delineation of transit-induced property value effects.

CRediT authorship contribution statement

Hisham Negm: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Rodrigo Victoriano-Habit:** Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis, Data curation, Conceptualization. **Mylene Riva:** Writing – review & editing, Validation, Project administration, Investigation, Funding acquisition, Conceptualization. **Ahmed El-Geneidy:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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