The Impact of Light Rail Transit Extensions on Residential Property Prices: Evidence from Dublin's Luas Cross City Project

A Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Bachelor of Arts (Honours)

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April 2024

Acknowledgements

First and foremost, I am indebted to my supervisor, Dr. Ronan Lyons, whose invaluable guidance and support have been instrumental throughout this study. I also extend my appreciation to Dr. Elisa Maria Tirindelli for her insightful perspectives on the causal analysis of transport infrastructure, and to Dr. Martina Kirchberger for igniting my curiosity in this field. I am immensely grateful to Ms. Cara O'Donoghue, whose guidance not only sparked my interest in economics but also inspired me to pursue it as a field of study

My heartfelt thanks go to my parents, whose creation of a supportive home environment has consistently encouraged me to pursue my aspirations, and to my sister and friends for their patience in enduring my discussions on the nuances of the Dublin housing market and the profound effects of public transit.

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1 Abstract

This study assesses the impact of the 2017 Cross City Luas (light rail) extension on residential property prices in North Inner City Dublin, Ireland, using Hedonic, Difference-in-Differences, and Instrumental Variable methods. The results present a robust and nuanced perspective on the value attributed to Luas access, revealing varying price effects contingent upon distance. This paper marks the first analysis of the house price effects of Luas proximity in the historically disadvantaged North Inner City, and improves upon prior literature by instrumenting the endogenous placement of Luas stops. As government departments consider the adoption of Transit-Oriented Development and the construction of Ireland's first metro (MetroLink), these results provide crucial insights for policymakers regarding the unintended consequences of such developments.

2 Introduction

This paper examines the residential property price effects of the 2017 Cross City extension of Dublin's Luas light rail system into the less-affluent North Inner City. In any urban area, public transit infrastructure plays a crucial role, impacting aspects of urban development including land use, sustainable development, and social equity. However, the development of transit systems can spur gentrification and increase local property prices (Shaw 2008). This is an important consideration, as Irish government departments have recently highlighted Transit-Oriented Development (TOD) as an approach for urban development, focusing on fostering walkable communities around high-quality public transit, and more than three-quarters of these planned developments lie in disadvantaged areas (DoHLGH and DoT 2023). In addition to this, the country's first metro system, again aimed at serving the city's northside, is moving into the advanced planning stages (Department of Transport 2022). Thus, understanding the dynamics between the expansion of public transit systems into this area, and the unintentional effects such as the impact on residential property prices, is essential for planners and policymakers.

As per the European Environment Agency (2006), Dublin is a prime example of urban sprawl. Planned mass-suburbanisation of the working class in the 20th century (McManus 2003) and large-scale Celtic Tiger-era construction on the city's fringes (Ahrens and Lyons 2019) have contributed to extensive low-density expansion, which has led to increased car use, longer commutes, and higher emissions. TOD offers a solution by promoting denser, mixed-use areas around transit hubs, which enables cities to accommodate growth without contributing to urban sprawl, traffic congestion, and pollution, thus preserving natural landscapes and minimising the environmental impact of urbanisation (Danielsen, Lang, and Fulton 1999). Hence, the development of the city's transit systems, such as the Luas, emerges as a critical intervention in mitigating the pervasive issues stemming from Dublin's problematic urban expansion.

The link between transit and equity is also well established. Chetty and Hendren (2018), for example, reveal a strong correlation between commuting times and social mobility in the US. The authors observe that low-income families in areas with more urban sprawl, and longer commuting times, face lower chances of escaping poverty. Additionally, Pathak, Wyczalkowski, and Huang (2017) highlight that enhancing public transit in less-central areas can help decentralise poverty by improving access to mobility and opportunities, though the effectiveness of public transit for disadvantaged groups is often limited by service distribution, affordability, and alignment with community needs (Zimmerman 2005). The North Inner City, where the majority of the extension lies, is an area of long-standing deprivation that has been masked in recent years by an influx of wealthier residents (Haase 2009), (see Figure 1) (Pobal 2024). Due to this, the extension of the Luas into this area represents a significant opportunity to enhance social equity and inclusion.

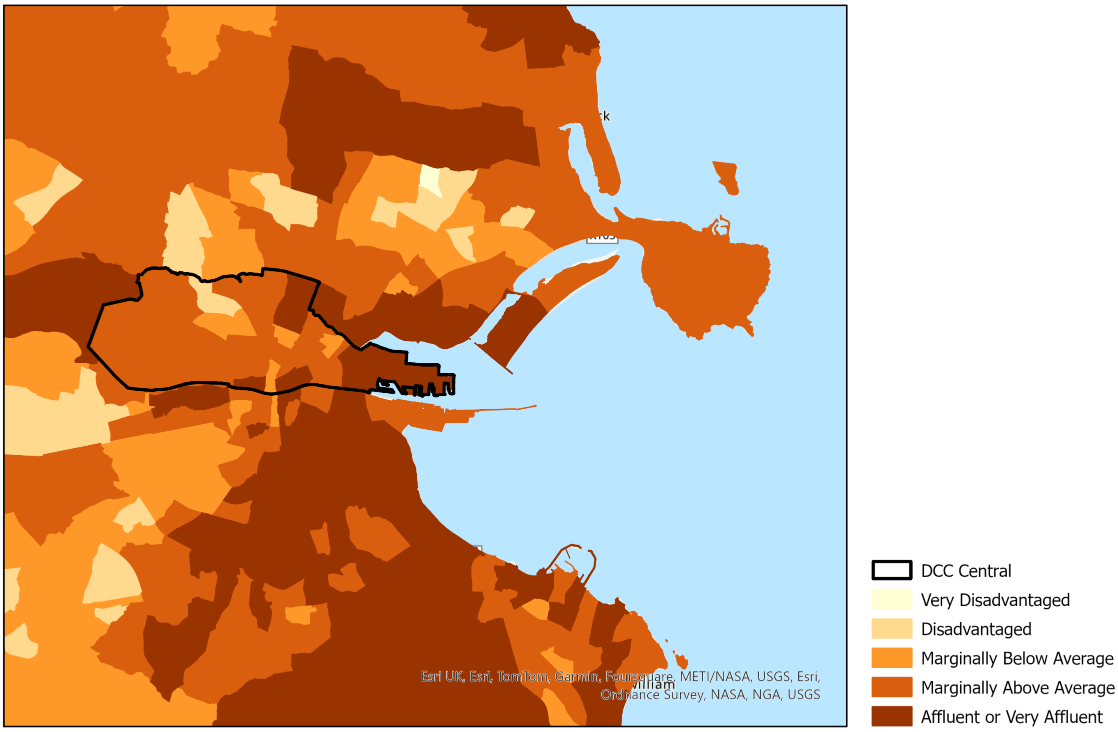

Figure 1: Levels of Disadvantage in Central Dublin

Transit developments, however, may contribute to gentrification, leading to increased local property prices and the displacement of vulnerable groups (Shaw 2008). Tirindelli (2023) observed that following the initial launch of the Luas in 2004, a 10% increase in an area's market accessibility resulted in a 5% decrease in the lower-skilled population, while concurrently witnessing a 7% increase in the population with higher skill levels. In the U.S., Chava and Renne (2022) highlight a similar pattern of minority and low-income displacement, indicating that while these infrastructures improve connectivity to services and jobs, they may also limit accessibility for marginalised communities. This underscores the critical need for Dublin and other cities that are expanding their public transport systems to carefully evaluate the broader impacts of such infrastructure, such as the property price and displacement effects (Padeiro, Louro, and Costa 2019).

As this study focuses on evaluating the impact of the northside Cross City Luas extension on residential property prices, the Dublin City Central Council Area, where the majority of the extension is situated, is the area of interest (see Figure 3) (Curtis 2019). The Luas, Ireland's only light rail system, serves Dublin city centre and some select suburbs. Commencing operations in 2004, the Luas reintroduced tram services to Dublin for the first time since 1959 (Scannell 2006). Between 2009 and 2011, the system was expanded thrice to better connect the south and south-western suburbs, Dublin's Docklands, and International Financial Services Centre (Transport Infrastructure Ireland 2017). The most recent extension in December 2017, seen in Figure 2, marked the first time that the Luas served the northside beyond the immediate city centre (Sinopluoglu 2017).

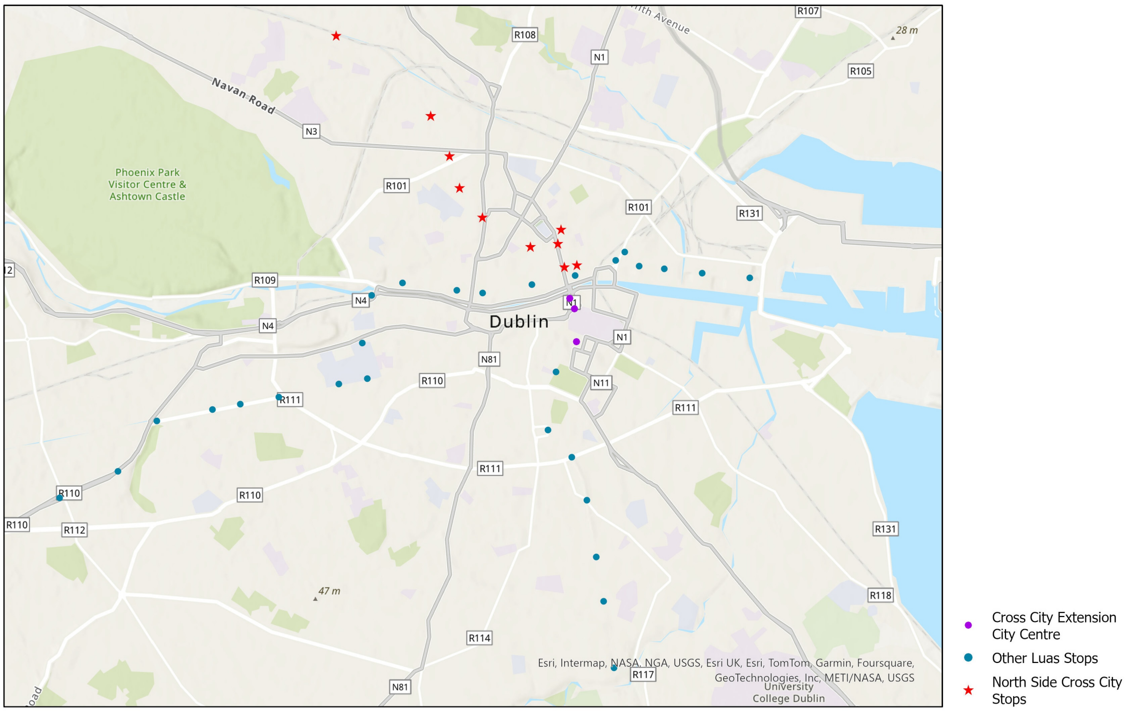

Figure 2: Luas Stop Map

Whilst Mayor et al. (2012) and Connor (2023) have previously explored the impact of the Luas and other rail infrastructure on residential property prices in Dublin, this paper advances their work by providing a robust estimation of the sales price effects of Luas proximity, and presents the first causal analysis of the specific effects of the Cross City Luas extension on the northside in isolation. Mayor et al.'s use of a hedonic price model may have encountered biases due to omitted variables, and both previous studies fail to address the presence of endogeneity in the location of the transit stops. To refine these insights, this study employs both Difference-in-Differences (DiD) and Instrumental Variable (IV) models to supplement a Hedonic analysis, with DiD addressing omitted variable bias and IV targeting endogeneity issues due to the likely non-random placement of Luas infrastructure. Furthermore, the focus on the historically less-affluent North Inner City may shed light on the differential property price effects of transit proximity due to local factors (Lee 2024). The research leverages data scraped from Daft.ie, Ireland's main property listing service, which includes details such as sale prices, addresses, and property specifications. A historic rail route is utilised as an instrumental variable in the IV model to isolate the causal effects of Luas proximity on property prices, offering a comprehensive understanding of public transit's unintended influence on Dublin's housing market in a more robust manner.

The hedonic model reveals that properties within 800 to 1000 metres of a new stop experienced an 8.11% price premium, the only statistically significant effect observed, highlighting a specific zone where proximity to public transit increases property values.

The DiD analysis further confirms the positive impact of the Luas extension on property values with properties within 1000 metres of a Luas stop exhibiting a 5.78% price premium. Finally, the IV model suggests a nuanced effect, with the only statistically significant effect being that of properties 400 to 800 metres from a stop, commanding a 13.1% premium. This may indicate a “Goldilocks zone”, where distance from transit strikes an optimal balance between accessibility and any negative externalities, whether realised or perceived, that may arise in close proximity to stations.

Building upon previous studies (Mayor et al. 2012; Connor 2023), this paper investigates the house price premiums of the recent extension of the Luas in Dublin, extending to provide robust estimates of these effects through instrumenting the endogenous placement of the stations. With a distinctive emphasis on the historically less-affluent North Inner City, this analysis offers insights into the broader implications of infrastructure development on urban areas which may be vulnerable to transit-induced gentrification, as well as the possible differing price impacts for lower-income localities (Lee 2024). As more than three-quarters of the zones designated for TOD in the city fall within disadvantaged zones, this paper delivers crucial insights for planners and policymakers focusing on infrastructure projects such as the new metro system (MetroLink) and other strategic developments within the city (DoHLGH and DoT 2023).

The remainder of this paper is structured as follows: Section 3 reviews the relevant literature, Section 4 discusses the context and the data employed in the analysis, Section 5 details the empirical strategies utilised in the study, Section 6 presents the results of the analyses, and Section 7 concludes the paper.

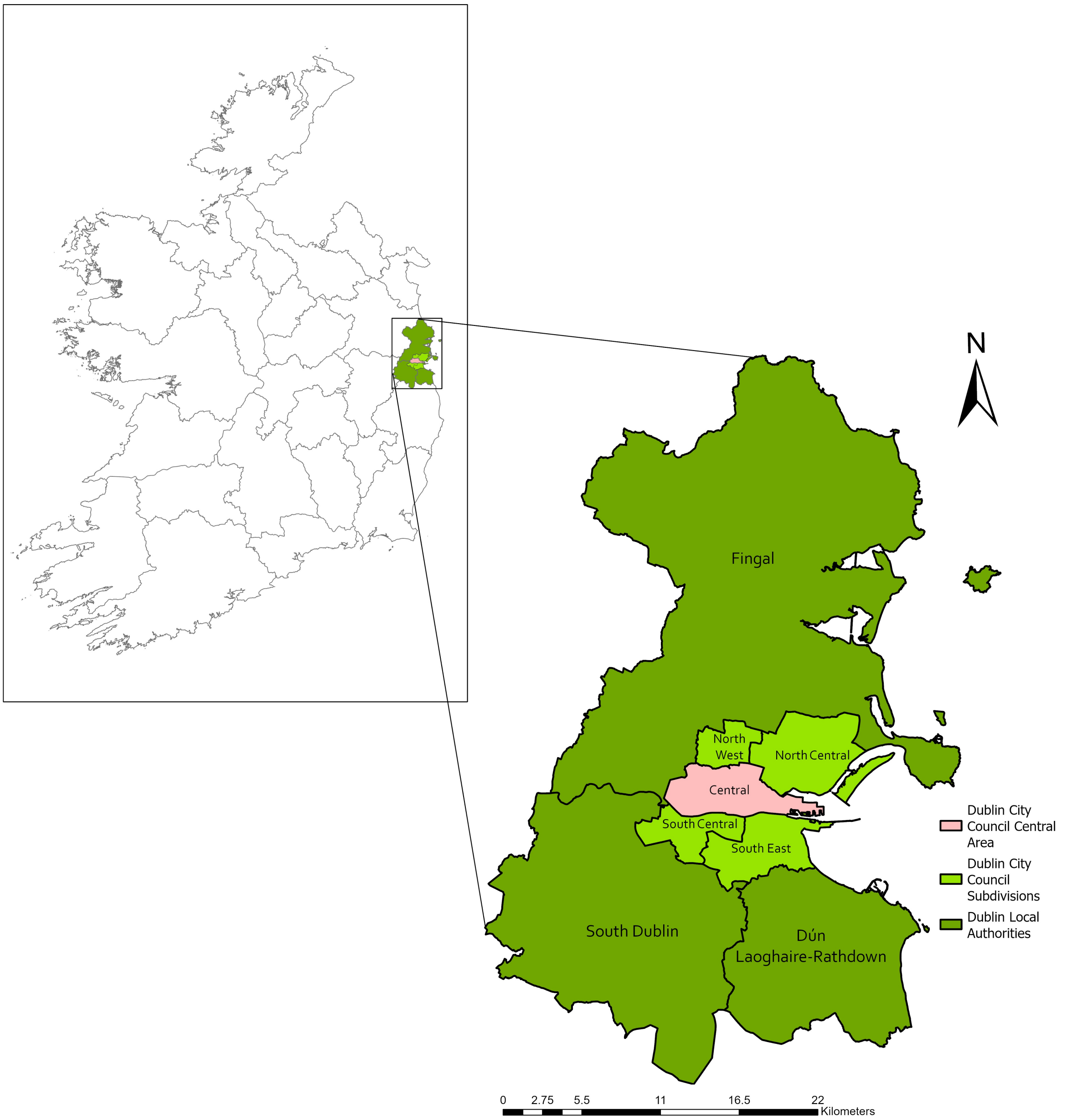

Figure 3: Study Area

3 Literature Review

There have been numerous studies that have assessed the effect of rail infrastructure on property prices, with varying results. These studies underscore the potential for significant price premiums associated with proximity to rail access, while also acknowledging instances of negligible or even adverse effects on property values. Considering the literature's focus on the US, it is essential to acknowledge the caveat related to higher car dependency in American cities compared to European cities (Kenworthy and Laube 1999). Consequently, Dublin residents may place greater value on increased access to public transit.

Chen et al. (2019) and McDonald (2004), for example, both find significant price premiums for properties in proximity to rail infrastructure in Sydney and Chicago. In Europe, Brandt and Maenning (2012) reveal a 4.6% price premium for properties in Hamburg located between 250 and 750 meters of a rail station, though the effect for those within 250 metres of stations is not significantly different from zero. In line with the conclusions reached by Brandt and Maenning (2012), other studies have found that the positive impact of rail infrastructure is not uniform across distances. Both Bowes and Ihlanfeldt (2001) and Lieske et al. (2019) observe price discounts for properties within approximately 400 metres of rail stations in Atlanta and Sydney respectively, though find price premiums for properties slightly farther away.

The dynamic between station proximity and property value can be further complicated when considering rail line extensions and the opening of new stations. Camins-Esakov and Vandegrift (2018) and Acuña (2023) study a line extension in New Jersey and the opening of new stations in Washington D.C. respectively, and uncover potential diminishing returns or disamenities associated with proximity to these to rail lines. Acuña (2023) does not limit her analysis to properties within walking distance to the new stations, as each station has associated Park and Ride facilities. The Luas stops examined in this paper, however, do not have any dedicated parking, thereby narrowing the purview of this analysis to properties that are accessible on foot. In contrast to both Camins-Esakov and Vandegrift (2018) and Acuña (2023), the analysis conducted in this paper employs a categorical measure of distance, rather than an unrestricted distance specification in order to assess the nuanced effect of distance, such as the possible negative effect for proximate properties, which may become positive as distance increases. When considering more than one new line, it is possible that effects may vary across the different developments. He et al. (2023), for example, examine two new lines in Shenzhen, China, and find a 5.9% price premium for properties in proximity to one line, though the effects of the other are insignificant. Again, the authors observe price discounts of up to -12.9% for properties within 200 metres of a station. Like He et al. (2023), this paper considers properties within 1000 metres of a Luas stop as treated in the hedonic-DiD specification (see Section 5.2).

Regarding the literature on public transportation in Dublin, Mayor et al. (2012) find that properties within 2000 metres of a Luas station command price premiums of up to 17%, representing the most significant price effect among all rail systems in the city. Connor (2023), who looks specifically at the property price effects of Luas proximity, identifies an average 12.6% price premium for residences located within a 20-minute walk of new Luas stations. Though Dublin is relatively well-served by bus routes, a recent investigation into Irish commuter behaviour by O'Driscoll et al. (2024) reveals a noteworthy trend: the presence of local rail stations, including the Luas, tends to reduce the use of bus systems, indicating a general preference for rail over other forms of transport. In relation to the Luas, the Cross City extension runs on dedicated lines from the terminus at Broombridge until it reaches the city centre, avoiding most traffic-related issues (Sinopluoglu 2017). In the context of this paper, this insight supports the hypothesis that enhanced public transport connectivity could lead to increased property values in areas serviced by the Luas extension, due to revealed commuter preferences.

Remarkably, Mayor et al. (2012) find no significant difference between anticipation and opening effect premiums when time discounting is taken into account. This is supported by Noh and Li (2022) in Los Angeles and Connor (2023) in Dublin, who observe a lack of statistically significant effects before the stations became operational. Regarding announcement effects, Kauria (2021) specifically highlights the issue of information asymmetry concerning the expected start of operations, given that the planned commencement is often several years in the future, and consequently, accurately forecasting outcomes can be challenging for the public. Thus, the analysis in this paper concentrates on the immediate post-operational effects of the Luas extension on nearby property prices.

The methodological approach of study diverges from the hedonic model used by Mayor et al. (2012) in their analysis of the property price effects of rail transport in Dublin. By incorporating both DiD and Instrumental Variable (IV) analyses, this paper provides more accurate estimates where omitted variable bias and endogeneity are concerned. As outlined by Duncan (2011), DiD offers a more robust framework for assessing the relationship between housing costs and proximity to public transit by addressing omitted variable bias. Building upon Connor's (2023) DiD model, IV analysis refines this approach by addressing the endogeneity in the placement of the Luas stops, thereby providing a more precise estimation of the impact on proximal property prices. As per a recent working paper by Fajgelbaum et al. (2023) political preferences can guide the location of transit stations, contrasting with an apolitical design that would focus on other aspects, such as metropolitan proximity. Thus, the analysis conducted in this paper presents the first robust examination of the Luas light rail system's impact on housing prices through a lens that considers the methodological rigour of DiD and IV analyses, with a specific focus on the North Inner City. This area, set to benefit from the upcoming MetroLink project, serves as a focal point for understanding the broader implications of such transport initiatives on urban housing markets. Further methodological processes are detailed in Section 5.

4 Context and Data Description

4.1 Context

For context, it is important to note the historical factors that have shaped Dublin's property market. The divergence between North and South Dublin, geographically divided by the River Liffey, reflects a deep-rooted division. McManus (2018) details how Dublin's unique socio-religious and political dynamics led to a pattern of social and spatial segregation, with middle-class Protestants and Unionists relocating to independently governed southside suburbs post-Catholic Emancipation. Wallace (2016) discusses the challenges faced by the city in delivering basic services, including the provision of new housing and addressing the conditions of slums, due to insufficient funding and dwindling tax revenues. Doherty, O'Leary, and Hynes (2015) highlight the enduring impact of this segregation, exacerbated in recent years by increasing affluence in the southside. South Dublin remains the most expensive property market in the city, with average sale prices in its most affluent area still 63% higher than those in the most expensive area of North Dublin. (Central Statistics Office 2023). Furthermore, Dupré (2020) finds that socio-economic characteristics of Dublin areas explain up to 43% of property price variance, highlighting the impact of area status on housing values. These dynamics provide critical context for this paper's investigation into the property price effects associated with the Luas light rail extension into the historically marginalised North Inner City.

4.2 Property Sales Data

The data concerning property sales was scraped from the property price register section of Daft.ie. The dataset encompasses key variables such as the property's address, sale price, sale date, property type, and the respective number of bedrooms and bathrooms. Including only complete entries, the dataset for County Dublin contains 44,894 sales, spanning from the register's establishment in January 2010 to the latest update in May 2021. As Daft.ie is Ireland's largest property website, this single source provides an extremely valuable insight into the market as a whole (Daft Inc. 2024).

Property size in square metres is not a commonly used metric in Ireland (Gillespie, Lyons, and Hynes 2023), and thus size is represented by categorical variables derived from the count of bedrooms and bathrooms, where each unit is transformed into a composite categorical value (bedrooms multiplied by 10, plus bathrooms). The analysis excludes properties with more than seven bedrooms or seven bathrooms in an effort to mitigate the effect of outliers which may represent a more niche segment of the market. In addition to this exclusion criterion, properties with sale prices of more than €1.5 million, or less than €50,000 are not included in this analysis, both to mitigate the effect of outliers and exclude properties sold at prices other than market value, e.g. foreclosures. Property type is also captured through categorical variables for type of dwelling.

With regards time trends, a series of quarterly categorical variables are also introduced, from $Q1\_2010$ to $Q2\_2021$, to control for short-term temporal variations and seasonal effects within the market. In regressing these dummies on the natural logarithm of sale price, the trend in the coefficients, relative to $Q2\_2021$, show largely negative coefficients from 2010 to 2013, as the Irish property market suffered due to the fallout of the collapse of the property bubble and the subsequent recession and sovereign debt crisis (see Figure A1 in the Appendix). The subsequent recovery is also evident through the positive coefficients in more recent years.

The data from Daft.ie offers text addresses only, and therefore, the observations were geocoded using the Geocoding API by Google. In taking exact coordinates of properties, issues with postcode mislabelling can be avoided and the analysis can be conducted at a more granular level. In their analysis of Irish property prices, Hurley and Sweeney (2022) find that 16% of the property listings in their dataset were advertised in the wrong postcode, with the majority of incorrect addresses listed as being in more affluent neighbouring areas. With the exact location of each property, the observations could then be attributed to the correct Electoral Division, the smallest legally defined administrative areas in the country (Central Statistics Office 2017). These administrative areas act as location controls, to capture the effect of area-specific characteristics that are not accounted for by other variables. Figure A2 in the Appendix presents the coefficients for these Electoral Divisions when regressed on the natural logarithm of sale price, relative to that of the North Inner City. Despite the very specific area of study, there remains noticeable variation in coefficient values. Drumcondra (Botanic C) emerges as the most expensive area, with a price premium of 83.13% and Broombridge (Cabra West A) is the least expensive with a 40% discount. Finally, the observations were subset for only those within the Central Council Area — for a total of 2,301 observations (see Figure A3 in the Appendix).

4.3 Luas Data

The 2017 northern extension of the Green Line of the Luas — Ireland's only light rail system — is contained entirely within the Dublin City Council Central Area. After taking the coordinates of the Luas stops, the Euclidian distance between each property and its closest station were added to the dataset. From this, the properties were categorised into three dummy distance bands relative to their nearest Luas stop: within 400 metres, between 400 to 800 metres, and between 800 to 1000 metres. Using categorical rather than unrestricted measures of distance allows for the examination of non-uniform effects for different distances, as exhibited in Bowes and Ihlanfeldt (2001), Brandt and Maenning (2012), and Lieske et al. (2019), for example. In addition to this, the properties were allocated to either the treatment or control group for further analysis, with those located within 1000 metres of a Luas stop designated as the treatment group, as per He et al. (2023). Considering properties within 1000 metres of a Luas stop as treated is also supported by Irish national planning guidelines, which advocate for higher densities within a 1000 metre radius of light rail stops (DoHLGH 2009). A final Luas-related variable concerns the sale date of the properties. If the property sale took place after the 9th of December 2017 — the date that the new stations opened — $sold\_after\_opening$ is equal to one, otherwise, it equals zero. This variable allows for the examination of any potential impact the opening of the new Luas stations had on treated property prices.

Table 1 presents the descriptive statistics for the relevant sample of properties, and Table 2 presents the descriptive statistics of sale prices by distance category.

Table 1: Descriptive Statistics of Key Variables

Variable	Mean	St. Dev.	Min.	Max.	Obs.
Price	€307,349.20	€151,846.90	€50,001	€1,350,000	2,301
Log Price	12.52	0.48	10.82	14.12	2,301
Distance to Luas	1,029.83	545.09	34.22	2,408.01	2,301
Bedrooms	2.47	0.96	1	6	2,301
Bathrooms	1.40	0.71	1	6	2,301

Table 2: Descriptive Statistics of Sale Prices by Luas Proximity

Category	Mean	St. Dev.	Min.	Max.	Obs.
luas0_400	€250,397.30	€114,844.40	€50,001	€1,050,000	370
luas400_800	€267,512.20	€120,021.30	€57,000	€1,000,000	484
luas800_1000	€291,162.00	€155,291.10	€60,000	€1,055,000	285
luas_treated_1000	€267,870.10	€129,011.70	€50,001	€1,055,000	1,139
luas_untreated_1000	€346,046.80	€162,283.40	€52,320	€1,350,000	1,162

5 Empirical Strategy

5.1 Hedonic Model

Hedonic price theory, introduced by Rosen (1974), posits that variation in prices of goods reflect consumers' willingness to pay for the specific array of characteristics attributed to the good. In the context of property price evaluation, the use of this model assumes that consumers derive utility – and value, from the characteristics of a property, and that the value of such utility can be priced (Malpezzi, Ozanne, and Thibodeau 1980).

The hedonic price function typically takes the following form, though can vary depending on the aim and the context of the analysis:

$$\text{Price} = f(S, L, E) + \varepsilon,$$

Where the price of a property is a function of its physical or structural characteristics, neighbourhood or location-based attributes, environmental characteristics, and the error term. The simplistic nature of the hedonic model lends itself well to a variety of functional forms, and though Rosen (1974) does not specify a particular form, non-linear models, particularly with a logarithmic transformation of the price variable, have become popular in the literature as they allow for flexibility in implicit prices (Chin and Chau 2003). Simplicity in functional form is also favourable. Cropper, Deck, and McConnell (1988) explore the optimal form for hedonic models, concluding that simpler forms often exhibit superior empirical performance. The authors also note that the ability to measure the marginal contribution of characteristics can differ based on the selection of a particular functional form.

The resulting coefficients from a hedonic model can be interpreted as the marginal willingness to pay (MWTP) for each attribute. This interpretation is foundational, as it contrasts with traditional supply and demand models, where the price of a good is exogenous, and the consumer, as a price taker, decides how much to consume based on the price. Non-linear hedonic models, however, introduce a scenario where the price fluctuates with quantity. In this model, the consumer has the flexibility to select both the quantity that they purchase and the price they pay (Sirmans, MacPherson, and Zietz 2005). Another underlying assumption of the results of Rosen's (1974) model is that the market is in equilibrium. However, the housing market — characterised by fluctuations, bubbles, busts, and cyclical patterns — leads some scholars to argue that hedonic coefficients are better understood as "implicit prices" rather than as measures of MWTP, particularly during phases of instability (see Lyons 2013; Zabel 2015). Nevertheless, hedonic pricing models have been applied extensively to the study of property prices globally (Chin and Chau 2003).

In accordance with the literature, the hedonic model specification in this paper takes a semi-log form, with a natural logarithmic transformation of sales prices:

$$\log(Y_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \sum_{k=1}^{3} (X_{4i} \times X_{5i})\gamma_k + \varepsilon_i$$

Where:

- Y_i is the natural logarithm of the sale price of $property_i$.
- X_{1i} is a vector of property-specific attributes for $property_i$, which includes property size and type controls.
- X_{2i} is a vector comprising of location-specific controls for $property_i$ at the level of the Electoral Division.
- X_{3i} is a vector of quarterly controls which account for time-trends.
- X_{4i} is the vector which represents the regressors of interest, with dummy variables representing the Euclidean distance from $property_i$ to the closest new Luas stop:
  - $D1_i$ for less than 400 metres
  - $D2_i$ for between 400 and 800 metres
  - $D3_i$ for between 800 and 1000 metres

  The reference category is implicitly coded as properties beyond 1000 metres.
- X_{5i} is a binary variable indicating whether $property_i$ was sold before $(= 0)$ or after $(= 1)$ the new Luas stations became operational.
- $\sum_{k=1}^{K-1}(X_{4i} \times X_{5i})$ is an interaction term between X_{4i} and X_{5i}, which captures the differential impact of the proximity of $property_i$ to its nearest Luas stop depending on whether the sale occurred before or after the new stops opened.
- ε_i is the error term, which captures unobservable factors that affect the sale price of $property_i$.

One issue with the above specification are the problems of omitted variable bias and endogeneity. With regards omitted variable bias, it is possible that the hedonic model fails to capture all relevant characteristics that influence property prices, leading to biased or incomplete estimates (Haan and Diewert 2013). Attention has also recently been drawn to the issue of endogeneity, or potential correlation between unobservables and the attribute(s) of interest in standard hedonic models, rendering causal analysis problematic in some instances (Greenstone 2017). In this case, the process that led to the specific placement of the new Luas stops may be non-random and related to unobserved factors that also affect property prices. Redding and Turner (2015) discuss this issue in depth in relation to the causal estimation of the impact of transportation infrastructure. The authors note that the use of instrumental variables for the placement of transport improvements, which satisfy the exclusion restriction by affecting the outcome of interest solely through the transport improvement, can be used to address biased estimates due to endogeneity concerns. The use of Instrumental Variable (IV) analysis in this paper is explained further in Section 5.3.

5.2 Difference-in-Differences Model

The logic unpinning the quasi-experimental difference-in-differences (DiD) model can be traced back to John Snow's (1855) analysis of the causes of cholera mortality. Snow (1855) exploited the change in the water supply in one area of London to compare the cholera mortality rates before and after the intervention, effectively utilising a natural experiment to infer causality. In modern econometrics, DiD is used to estimate the causal effect of an event, such as a policy intervention. By contrasting groups that are exposed to the intervention (treatment groups) with those that are not (control groups) across both pre- and post-event periods, the underlying assumption is that had the event not occurred, the differences between these groups would have remained the same (Lechner 2011).

DiD models typically take the following form:

$$Y = \beta_0 + \beta_1 \text{Treatment} + \beta_2 \text{Post} + \beta_3 (\text{Treatment} \times \text{Post}) + \varepsilon$$

Where:

- Treatment is a binary dummy variable equal to one for the treatment group, and zero for the control group.
- Post is a binary dummy variable indicating the pre-treatment (=0) and post-treatment (=1) periods.
- Treatment $\times$ Post is a binary dummy variable which represents the interaction between the two variables. This interaction term is crucial to the model, as it estimates the differential effect of being in the treatment group after the intervention compared to before the intervention, effectively isolating the causal impact of the treatment.

In interpreting the coefficients:

- β_1 represents the treatment group effect, accounting for the average permanent differences between the treatment and control groups.
- β_2 captures the general time trend affecting both groups.

- β_3 is the coefficient for the interaction term, which is key to identifying the differential effect of the treatment over time, isolating the causal impact of the treatment.

Since the publication of Snow's (1855) analysis, DiD has become one of the most commonly-used methods to estimate effects of policy change and interventions in empirical microeconomics (Lechner 2011). In recent years, DiD has also been used as a framework in the context of hedonic models to address biases arising from unobserved factors that are correlated with the amenities of interest (Banzhaf 2021). Atreya and Ferreira (2015), for example, combine the methods in order to estimate variation in implicit flood risk premiums following large inundation events. Banzhaf (2021) finds that these methods can accurately identify the "average direct effect" of changes in amenities on property prices. This effect is observed as a shift along the price curve following the event, providing a lower-bound estimate of the actual economic value (or Hicksian equivalent surplus) due to such changes.

DiD estimation rests on the parallel trends assumption, which supposes that the treatment group would have followed the same time trend as the control group should no intervention have taken place (Fredriksson and Oliveira 2019). Both unobservable and observable factors may cause differences between the level of the outcome variable for the treatment and controls groups, though this difference is required to remain constant over time. Figure 4, presents a graphical example of this assumption, where the control and treatment groups are moving in parallel before the policy intervention, and diverge in the post-intervention period. Though visual support can serve as evidence that this assumption holds, more formal methods have also been developed. Gertler et al. (2016) suggest the use of a "move-in-tandem" test, with the assumption that if the outcomes of the treatment and control groups were moving in tandem before the intervention, one can have confidence that outcomes would have continued to move in tandem in the post-treatment period without any intervention. This test requires at least two serial observations of both the treatment and controls groups before the intervention. In practice, this test involves the creation four subsets of data: a treatment group before the event, a treatment group after the event, a control group before the event, and a control group after the event. By regressing the time trend on the desired outcome variable for each of these four sub-data sets, one can compare the trends in treatment and control groups in both periods.

The hedonic-DiD analysis in this paper allows for the estimation of the causal price effect of the opening of a new Luas stop within 1000 metres of a property (as per He et al. 2023), with this distance category specified as the treated group. The "move in tandem" test, as specified below, is used to assess the validity of the parallel trends assumption:

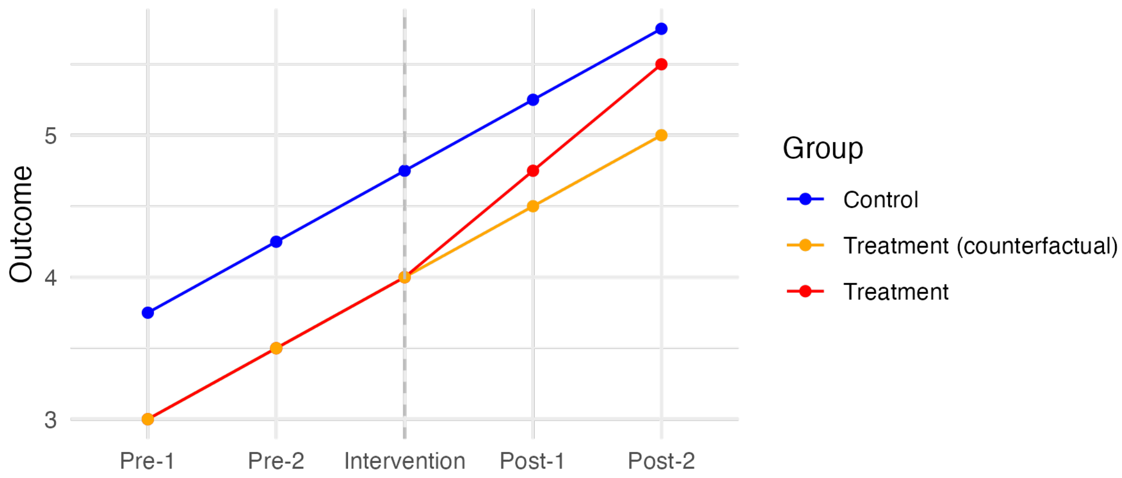

Figure 4: Parallel Trends Assumption

$$log(Y_i) = \beta_0 + \beta_1 X_{1i} + \varepsilon_i$$

Where $\log(Y_i)$ is the natural logarithm of the sale price of $property_i$, and X_{1i} is the sale date of $property_i$. This analysis is conducted for both the treatment and control groups, firstly for those sold before the stations opened, and secondly for those sold after the stations opened. The models are compared in the pre- and post-treatment periods.

The hedonic-DiD specification used in this paper broadly follows the approach of Atreya and Ferreira (2015).

$$log(Y_i) = \beta_0 + \beta_1 \text{Treatment}_i + \beta_2 \text{Post}_i + \beta_3 (\text{Treatment}_i \times \text{Post}_i) + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \varepsilon_i$$

Where:

- Y_i is the natural logarithm of the sale price of $property_i$.
- Treatment_i is a binary dummy variable indicating treatment, equalling one if $property_i$ lies within 1000 metres of a new Luas stop, and zero otherwise.
- Post_i is a binary dummy variable, equalling one if $property_i$ was sold after the new Luas stops became operational, and zero otherwise.
- $\text{Treatment}_i \times \text{Post}_i$ is the interaction term between the treatment and time indicators relevant to $property_i$. This captures the differential effect of being in the treatment group after the intervention compared to before the intervention, isolating the causal impact of the treatment.
- X_{4i} is a vector of property-specific attributes for $property_i$, which includes property size and type controls.

- X_{5i} is a vector comprising location-specific controls for $property_i$, at the level of the Electoral Division.
- X_{6i} is a vector of quarterly controls which account for time-trends.
- ε_i is the error term, which captures unobservable factors that affect the sale price of $property_i$.

This hedonic-DiD specification does not address the issues discussed in Section 5.1 regarding endogeneity in hedonic models, though it can assist with problems relating to omitted variable bias by controlling for both time-invariant characteristics that may differ between the treatment and control groups, and common trends affecting all observations over time. Due to endogeneity concerns, an IV analysis is employed to ensure that the relationship between the treatment and the outcome is not confounded by unobservables.

5.3 Instrumental Variables Model

Instrumental Variable (IV) analysis originates from Appendix B of The Tariff on Animal and Vegetable Oils, written by Philip G. Wright in 1928 (Morgan 1990). In contemporary econometrics, IV analysis is conducted as a Two-Stage-Least-Squares (2SLS) specification, where the first stage involves regressing the endogenous variable on the "instrument", a variable chosen to isolate exogenous variation in the problematic explanatory regressor. Following this, predicted values of the endogenous variable are obtained from the first stage model, which form the second stage of the analysis (Angrist and Krueger 2001).

The general notation for an IV specification is typically as follows:

First Stage:

$$X_i = \pi_0 + \pi_1 Z_i + \varepsilon_i$$

Where X_i is the endogenous variable, Z_i is the instrument, and ε_i is the error term.

Second Stage:

$$Y_i = \beta_0 + \beta_1 \hat{X}_i + \varepsilon_i$$

Where Y_i is the dependent variable, $\hat{X}_i$ represents the predicted values of the endogenous variable X_i obtained from the first stage (which is now, in theory, free of endogeneity concerns), and ε_i is the error term.

If supplementary exogenous variables are required for the analysis, they can be introduced in both stages.

There are two conditions that are necessary for an instrument to be valid: relevance and exogeneity (or validity). An instrument is relevant if $\text{corr}(Z_i, X_i) \neq 0$, and is exogenous, or valid, if $\text{corr}(Z_i, \varepsilon_i) = 0$. Once these conditions have been satisfied, the instrument can effectively be used in the IV analysis to provide consistent and unbiased estimates of the causal effect of the endogenous explanatory variable on the dependent variable.

There are also several statistical tests used to ensure the robustness of an IV model and the relevant instruments. The Durbin-Wu-Hausman (DWH) Test is a statistical method which tests for the presence of endogeneity in explanatory variables within a regression model, which would, to obtain unbiased causal estimates, necessitate the use of an instrument (Durbin 1954; Wu 1973; Hausman 1978). The test compares estimates obtained from OLS with those obtained from IV regression, and rejecting the null hypothesis that the variables are exogenous justifies the use of IV analysis. The DWH test does not assess the strength or relevance of the instrument, though this is commonly accomplished through the first-stage F-statistic, or Weak Instrument Test (Staiger and Stock 1997). Instruments are typically considered strong if this statistic is above 10, suggesting that the instrument has a significant correlation with the endogenous explanatory variable, thereby providing a reliable basis for the IV estimation to produce consistent and efficient estimates of the causal effect. If there are more candidate instruments than there are potentially endogenous variables in a model, Sargan/Hansen tests can be used to check for over-identification in the model (Kiviet and Kripfganz 2021). The diagnostic and robustness checks used in this analysis are discussed in Section 6.

Empirical analyses of the causal effects of changes in transportation infrastructure have employed a variety of different instruments to address the issue of endogeneity. Baum-Snow (2007) pioneered using planned routes as instruments for observed routes in assessing how new limited access highways contributed to central city population declines, assuming that locations with planned, but unbuilt, infrastructure should resemble those with completed projects based on pre-construction characteristics. The use of historical routes as an instrument is another common approach, as unobservables from the distant past should not be correlated with those of today. This method is used by Duranton and Turner (2011) to instrument modern transportation infrastructure. Thirdly, the inconsequential units approach is specifically useful when there are no historical or planned routes available, as seen in Tirindelli's (2023) analysis of the effect of the original Luas system on income and skill distribution in Dublin. Though Tirindelli (2023) uses a historical route for the Green Line of the Luas, the Red Line passes through previously agricultural land, for which no other instrument exists. By connecting the terminus of the Red Line with the city centre using a straight-line, least-cost-path approach, the author can isolate the effect of the tram system on local income and skill distribution without the confounding influence of pre-existing transportation infrastructure or planning biases.

The IV analysis in this paper is in line with that of Duranton and Turner (2011) and particularly with Tirindelli (2023), utilising a 1922-1923 railroad map from O'Rourke and the Dublin Civic Survey Committee (1925) as the instrument to isolate the exogenous effect of the Cross City Luas Extension. As seen in Figure 5, a significant section of the Luas line follows closely that of the old Midland Great Western Railway (MGWR), which terminated at Broadstone Railway Station, the location of the Broadstone Luas stop (Muldowney 2020). The lines between the Broombridge (terminus), Cabra, and Phibsboro stops are laid upon these disused tracks, whilst the Grangegorman and Broadstone stops remain close to the historic line. In the case of this model, the instrument is obtained by calculating the Euclidian distance from each property to the historical rail line. Properties are then allocated into binary variables with the same 4 categories: within 400 metres, between 400 to 800 metres, and between 800 to 1000 metres, with the reference category implicitly coded as properties more than 1000 metres from the historical rail line.

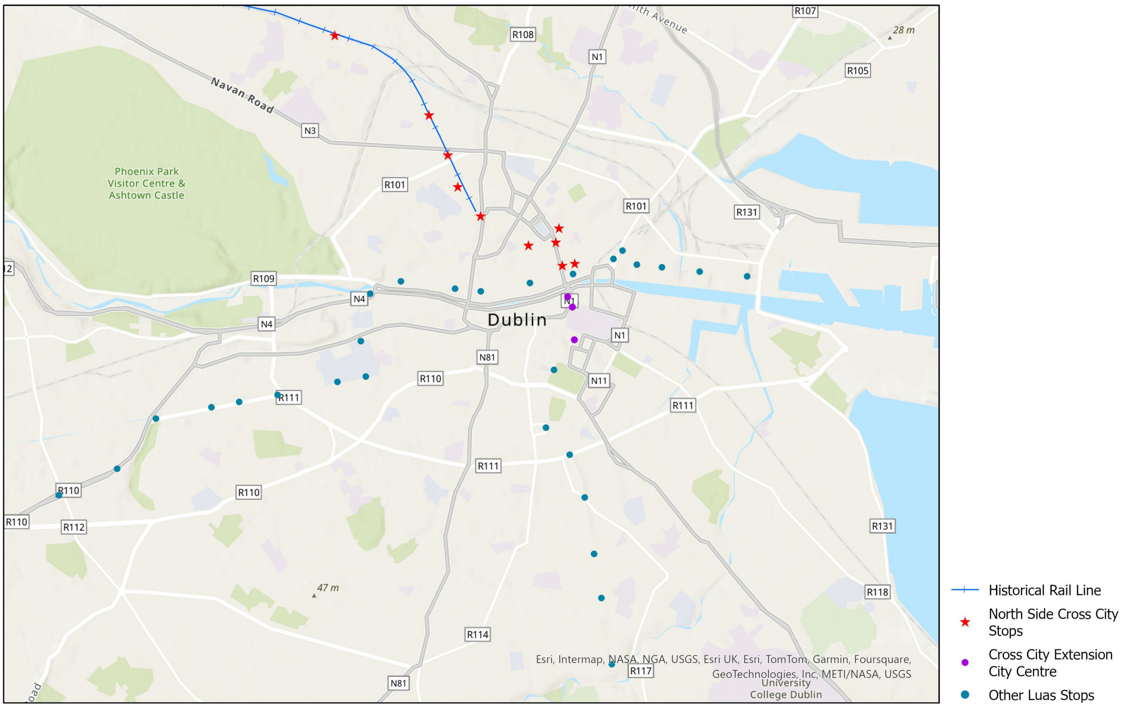

Figure 5: Luas Stop Map with Historical Train Line

First Stage:

$$X_i = \beta_0 + \beta_1 Z_i + \beta_2 X_{1i} + \beta_3 X_{2i} + \beta_4 X_{3i} + \beta_5 X_{4i} + \sum_{k=1}^{3} (Z_i \times X_{4i})\gamma_k + \varepsilon_i$$

Where:

- X_i is a vector of binary variables representing the Euclidean distance from $property_i$ to the closest new Luas stop:

- $D1_i$ for less than 400 metres
- $D2_i$ for between 400 and 800 metres
- $D3_i$ for between 800 and 1000 metres
- The reference category is implicitly coded as properties beyond 1000 metres.

- Z_i is the instrument, a vector of binary variables representing the Euclidean distance from $property_i$ to the closest part of the historical train line:
  - $ID1_i$ for less than 400 metres
  - $ID2_i$ for between 400 and 800 metres
  - $ID3_i$ for between 800 and 1000 metres
  - Again, the reference category is implicitly coded as properties beyond 1000 metres.
- X_{1i} is a vector of property-specific attributes for $property_i$, which includes property size and type controls.
- X_{2i} is a vector comprising of location-specific controls for $property_i$ at the level of the Electoral Division.
- X_{3i} is a vector of quarterly controls which account for time-trends.
- X_{4i} is a binary variable indicating whether $property_i$ was sold before $(= 0)$ or after $(= 1)$ the new Luas stations became operational.
- The interaction term $\sum_{k=1}^{3}(Z_i \times X_{4i})\gamma_k$ captures the differential impact of transit proximity depending on whether $property_i$ was sold before or after the new stops opened
- ε_i is the error term.

Second Stage:

$$log(Y_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 \hat{X}_{5i} + \sum_{k=1}^{3}(X_{4i} \times \hat{X}_{5i})\gamma_k + \varepsilon_i$$

Where:

- Y_i is the natural logarithm of the sale price of $property_i$.
- X_{1i}, X_{2i}, X_{3i}, and X_{4i} are as defined above.
- $\hat{X}_{5i}$ is the vector representing the predicted values of the regressors of interest, acquired from the first stage.

- The interaction term $\sum_{k=1}^{3}(X_{4i} \times \hat{X}_{5i})\gamma_k$ captures the differential impact of proximity to the nearest Luas stop depending on the sale's timing.
- ε_i is the error term.

6 Results

6.1 Hedonic Model

The results from the hedonic analysis, specified in Section 5.1, are presented in Table 3. Properties that lie within 400 metres of a new Luas stop that were sold after the stations became operational saw, on average, a 5.13% price premium relative to properties further than 1000 metres from their nearest station. This effect did not achieve statistical significance, aligning with the results of Brandt and Maenning (2012), who, in Hamburg, also observed non-statistically significant price effects for properties in close proximity to rail stations. Properties between 400 and 800 metres from their closest Luas stop that sold after the line opened see a similar price premium of 4.92%, on average, relative to properties further than 1000 metres from a station. Again, this result is not statistically significantly different from zero. Properties between 800 to 1000 metres of a new Luas stop that sold after the stations opened demonstrate the most substantial, and the only statistically significant, price effect in this model, with an observed 8.11% premium compared to properties beyond 1000 metres from their nearest station. This outcome aligns with the findings of Lieske et al. (2019), who identified positive price effects for properties situated within 900 to 1900 metres of rail infrastructure in Sydney. The lack of statistically significant effects for houses within 800 metres of the new stations in this model may be due to diminishing returns, as noted by Camins-Esakov and Vandegrift (2018), though disamenity effects of proximity may also play a role due to negative externalities. These results are less pronounced than Mayor et al.'s (2012) observation of price premiums of up to 17% for properties within 2000 metres of a Luas, though the authors do admit that their data disproportionally contains properties on the wealthier southside of the city, which may explain the increased magnitude of the price premiums that they observed. Lee (2024) also notes that the price effects of proximity to rail transit can vary based on the local context, which suggests that the varying socio-economic landscapes across different parts of Dublin could significantly influence the observed impact of Luas accessibility on property prices. This is supported by Dupré's (2020) finding that socio-economic characteristics of Dublin areas explain up to 43% of observed property price variances.

Regarding the goodness of fit, the hedonic model demonstrates a robust explanatory power, with an adjusted R^2 value of approximately 64.4%. This indicates that the model accounts for a significant proportion of the variance in the natural logarithm of property prices. Furthermore, the $F statistic$ of 32.542, significant at the 1% level, underscores the statistical reliability of the model.

As discussed in Section 5.1, the estimates from this hedonic model, though useful in determining the implicit prices attributed to property characteristics, may be biased due to omitted variable bias and endogeneity or selection into treatment. Thus, the estimates obtained through the DiD and IV models are likely to be much more robust.

Table 3: Hedonic Model Results

	Dependent variable:
	log(Price)
luas0_400*sold_after_opening	0.050
	(0.038)
luas400_800*sold_after_opening	0.048
	(0.034)
luas800_1000*sold_after_opening	0.078*
	(0.044)
Constant	12.397***
	(0.096)
Property Size Controls	Yes
Time Trend Controls	Yes
Neighbourhood Controls	Yes
Observations	2,301
R^2	0.644
Adjusted R^2	0.624
Residual Std. Error	0.296 (df = 2179)
F Statistic	32.542*** (df = 121; 2179)

Note: Coefficient estimates are interpreted as percentage changes in the dependent variable for a one-unit increase in the predictor variable, calculated using the formula $(e^{\beta} - 1) \times 100$.

*p<0.1; **p<0.05; ***p<0.01

6.2 Difference-in-Differences Model

As outlined in Section 5.2, the benefit of conducting a DiD analysis pertains to the fact that the risk of omitted variable bias is reduced as this design controls for characteristics that remain constant over time but vary between the treatment and control groups, along with trends that uniformly impact all observations throughout the study period. In lieu of a visual confirmation that the parallel trends assumption holds, this paper makes use of the “move-in-tandem” test under the premise that had the treatment and control groups’ outcomes been trending together prior to the intervention, it is reasonable to believe they would have maintained a similar trajectory in the absence of any intervention (Gertler et al. 2016). The results of the pre- and post-event analysis, specified in Section 5.2, are presented in Table 4 and 5, respectively. From these results, it is clear that in the pre-event period, the prices of control properties, situated more than 1000 metres away from the nearest Luas stop, were rising at twice the rate of those in the treatment group, with a high level of statistical significance

($p < 0.01$). In the post-event period, there is an insignificant and negligible change in log prices in the control group, implying a stagnation or minimal increase in the natural logarithm of sale prices after the event, whilst the treatment group continues to trend upward, significant at the 5% level. Given these results, the distinct divergence in trends post-event, as evidenced by the stagnation in the control group's property prices, sharply contrasts with the anticipated continuity of the pre-event growth trajectory. This change underscores the intervention's impact, suggesting that the Luas extension significantly influences property values within its vicinity.

With confirmation that the parallel trends assumption holds, it becomes feasible to employ a DiD model. This approach allows for the mitigation of omitted variable bias (OVB) that could have potentially led to biased or incorrect estimates in the hedonic model results from Table 3. Per the specification outlined in Section 5.2, the results of this analysis are presented in Table 6.

The estimate for $luas\_treated\_1000$ is not statistically significant, indicating that there was no significant difference in property prices between the treatment (within 1000 metres of a Luas stop) and control properties (further than 1000 metres from a Luas stop) before the Luas extension was operational. The coefficient for $sold\_after\_opening$ indicates that, on average, properties that sold after the Luas extension opened experienced a 31.78% higher sale price compared to those sold before the introduction of the line. This is statistically significant at the 1% level, and reflects overall market trends or other time-varying effects that are not solely attributable to the Luas extension. The estimate for the interaction term, $luas\_treated\_1000 * sold\_after\_opening$ captures the additional price change for properties within 1000 metres of a Luas stop after the extension became operational. The value of this coefficient is 5.78% and indicates that these properties commanded a price premium due to their proximity to the new Luas line, and the fact that they sold when the line was operating. This estimate is also statistically significant at the 5% level, reflecting the specific benefit of improved access to public transportation provided by the Luas, beyond general market trends, observed after the extension's opening.

The results of this analysis are broadly in line with the literature that employs hedonic-DiD models to isolate the causal price effects of proximity to rail transport. He et al. (2023), for example, find a 5.9% house price premium for properties within 1000 metres of a new metro line in Shenzhen, China, using a similar specification. In the Helsinki region, Kauria (2021) obtains comparable results, observing a 4.6% price premium for properties within 800 metres of the new Jokeri Light Rail system. The more modest results observed in this study, compared to Connor's (2023) finding of a 12.6% price premium for properties within a 20-minute walk of a Luas station, using a DiD specification, may be attributed to the influence of local socio-economic conditions on the magnitude of price premiums, echoing Lee's observations (2024).

Table 4: Move-in-Tandem Test Pre-Event

	Pre-Event Analysis	
	Dependent variable:	
	log(Price)	
	Treatment	*Control*
Time	0.0001^{***}	0.0002^{***}
	(0.00002)	(0.00002)
Constant	9.822^{***}	9.488^{***}
	(0.336)	(0.366)
Observations	747	767
R^2	0.066	0.082
Adjusted R^2	0.065	0.081
Residual Std. Error	0.449 (df = 745)	0.467 (df = 765)
F Statistic	52.718^{***} (df = 1; 745)	68.152^{***} (df = 1; 765)
Note:	Gertler et al. (2016)	
		*p<0.1; **p<0.05; ***p<0.01

Table 5: Move-in-Tandem Test Post-Event

	Post-Event Analysis	
	Dependent variable:	
	log(Price)	
	Treatment	*Control*
Time	0.0001^{**}	0.00003
	(0.0001)	(0.0001)
Constant	10.469^{***}	12.278^{***}
	(1.001)	(0.982)
Observations	400	495
R^2	0.012	0.001
Adjusted R^2	0.009	−0.001
Residual Std. Error	0.376 (df = 398)	0.407 (df = 493)
F Statistic	4.710^{**} (df = 1; 398)	0.293 (df = 1; 493)
Note:	Gertler et al. (2016)	
		*p<0.1; **p<0.05; ***p<0.01

With regards goodness of fit, the adjusted R^2 value of 62.5% indicates that the model accounts for a large amount of the variance in the natural logarithm of property prices. The $F statistic$ of 33.699, significant at the 1% level, again highlights statistical reliability of the model.

Though the estimates obtained from this hedonic-DiD model are more robust than the purely hedonic model in Section 6.1, endogeneity may still be a concern. As discussed in Section 5.3, much of the new Luas line follows very closely the old Midland Great Western Railway (MGWR) tracks (see Figure 5). Thus, it is highly plausible that the placement of the Luas stations is non-random, and likely reflect historical patterns of development or other unobservable factors that could have led to biased estimates in this model.

Table 6: Difference-in-Differences Model Results

	Dependent variable:
	log(Price)
luas_treated_1000	−0.043
	(0.030)
sold_after_opening	0.276***
	(0.081)
luas_treated_1000*sold_after_opening	0.056**
	(0.026)
Constant	12.412***
	(0.090)
Property Size Controls	Yes
Time Trend Controls	Yes
Neighbourhood Controls	Yes
Observations	2,301
R^2	0.644
Adjusted R^2	0.625
Residual Std. Error	0.296 (df = 2183)
F Statistic	33.699*** (df = 117; 2183)

Note: Coefficient estimates are interpreted as percentage changes in the dependent variable for a one-unit increase in the predictor variable, calculated using the formula $(e^{\beta} - 1) \times 100$.

*p<0.1; **p<0.05; ***p<0.01

6.3 Instrumental Variable Model

The results from the IV analysis specified in Section 5.3 are presented in Table 7. The coefficient for properties sold after the Luas stations became operational and located within 400 meters of a stop is -4.97%, which suggests that, on average, these properties sold at a discount relative to properties further than 1000 metres from a station. This finding is not statistically significant, indicating that there is insufficient evidence to conclude that the impact on prices for these properties differs from zero. Again, this result is in line with the findings of Brandt and Maenning (2012), who also observed non-statistically significant price effects for properties in close proximity to rail stations in Hamburg. In the context of this study, the increased accessibility of proximity to a Luas stop may be offset by perceived or realised anti-social behaviour or other negative externalities associated with public transit infrastructure.

Properties between 400 and 800 metres from a Luas stop that sold after the stations opened, on average, commanded a price premium of 13.1%, relative to properties more than 1000 metres from a Luas stop. This result is significant at the 5% level, suggesting that proximity to a Luas stop within the specified distance range significantly increases property values, reflecting the positive impact of the improved accessibility and connectivity provided by the Luas extension. This supports the results of Noh and Li (2022), who observed a “Goldilocks” zone, wherein properties at an intermediate distance from light rail stations in Los Angeles commanded large price premiums of as much as 10%. Whilst this finding is limited to middle- and high-income neighbourhoods, Brandt and Maenning (2012) also find maximum premiums at intermediate distances from rail stations.

Properties that sold after the Luas line opened, that are between 800 and 1000 metres from a station see, on average, a price discount of -3.63% relative to properties further than 1000 metres from a stop. This effect is again not statistically significant, and thus there is insufficient evidence to conclude that the price effect for these properties differs from zero. Interestingly, this result is again in line with Brandt and Maenning (2012), who find insignificant price effects initially as distance to rail access narrows to between 1,750 and 750 meters. These results also corroborate the findings of O’Connor and Caulfield (2018), who posit that the natural walking catchment threshold for Luas transit in Dublin is 825 metres.

With regards the diagnostic tests and robustness checks outlined in Section 5.3, the results of the DWH and Weak Instrument tests are presented at the end of Table 7. The DWH test, which tests for the presence of endogeneity in the model, has a $p - value$ of less than $2e - 16$, which is statistically significant at the 1% level. This result strongly suggests that the endogenous regressors are correlated with the error term, thereby justifying the use of instrumental variables to correct for potential biases in the estimates. Importantly, the Wu-Hausman aspect of this test checks if the IV model is just as consistent as the ordinary least squares (OLS) estimator. Since the test result is statistically significant, one can reject the null hypothesis, indicating that OLS is not consistent due to endogeneity. This affirms the relevance of using instrumental variables to address potential biases in the estimates. The $p - value$ for the Weak Instrument Test, which assesses the strength of the instruments, is $3.43e - 05$. This is again statistically significant at the 1% level, and thus, one can reject the null hypothesis that the instruments are weak and conclude that the instruments have a substantial correlation with the endogenous explanatory variables and provide reliable tools for identifying the causal effect. Sargan/Hansen tests are not relevant to this model, as there is only one instrument employed.

In relation to the goodness of fit of this model, the adjusted R^2 is 61.2%, which again indicates that a high level of the variance in the natural logarithm of sale price is explained by this model, underscoring the strong explanatory power of the model.

Table 7: Instrumental Variable Model Results

	Dependent variable:
	log(Price)
luas0_400*sold_after_opening	-0.051
	(0.073)
luas400_800*sold_after_opening	0.123^{**}
	(0.057)
luas800_1000*sold_after_opening	-0.037
	(0.074)
Constant	12.513^{***}
	(0.117)
Property Size Controls	Yes
Time Trend Controls	Yes
Neighbourhood Controls	Yes
Observations	2,301
R^2	0.633
Adjusted R^2	0.612
Residual Std. Error	0.300 (df = 2179)
Diagnostic tests:	
Weak instruments (luas_effects)	p-value $< 2e - 16^{***}$
Wu-Hausman	p-value = 3.43e-05***

Note: Coefficient estimates are interpreted as percentage changes in the dependent variable for a one-unit increase in the predictor variable, calculated using the formula $(e^{\beta} - 1) \times 100$.

*p<0.1; **p<0.05; ***p<0.01

7 Conclusion

This paper examines the residential property price impact of the 2017 Cross City Luas Extension in Dublin, Ireland, focusing on the North Inner City. Leveraging a comprehensive dataset sourced from Daft.ie, this analysis includes three separate empirical specifications with the aim of obtaining robust and unbiased estimates. This study represents the first thorough examination of the Luas Extension's influence on property prices, with a focus on the less-wealthy North Inner City, marking a significant contribution to the understanding of urban transit infrastructure's effects on local property markets.

Firstly, a semi-logarithmic hedonic analysis is employed, revealing that only properties located within 800 to 1000 meters of a Luas stop exhibit a statistically significant price effect, showing an 8.11% price premium at the 10% significance level.

To mitigate the risk of omitted variable bias, this study applies a DiD analysis. Considering properties within 1000 metres of a station as treated, the results reveal an additional price premium of 5.78% for treated properties that were sold after the Luas line became operational relative to the control group, with statistical significance at the 5% level. This method provides a more precise measurement of the extension's impact on property values by effectively accounting for external variables that could impact the results.

Finally, in order to address any endogeneity in the model which may result from the non-random placement of the new Luas stops, an IV model is employed. Using a historical route as the instrument to isolate the exogenous effects of Luas proximity, the results of this model reveal a 13.1% price premium for properties between 400 and 800 metres from a Luas stop that were sold after the line opened, statistically significant at the 5% level.

Overall, the findings from this study broadly corroborate, and expand upon, Mayor et al.'s (2012) identification of price premiums of up to 17% for properties near Luas stops, as well as Connor's (2023) observation of a 12.6% premium for residences within a 20-minute walk of new Luas stations. This research extends their work by employing a more robust IV model to account for the endogenous placement of Luas stops, and the focus on the less-affluent North Inner City, and observed smaller or less statistically significant price premiums, could be due to the area's socio-economic characteristics, as suggested by Dupré (2020). The lack of statistically significant effects for properties within 400 metres of a station may reflect negative externalities associated with proximity to the infrastructure. Furthermore, the lack of statistically significant price effects for properties beyond 800 metres from a Luas stop in the IV model supports the results of O'Connor and Caulfield (2018), who suggest that the natural walking catchment threshold for Luas stations in Dublin is 825 metres.

The results of this study have substantial policy implications for the city of Dublin as it faces the challenges associated with urban sprawl, including inefficient land use, social inequity, and patterns of development that are not sustainable. The development of public transit can assist in addressing these issues by promoting more efficient, equitable, and sustainable urban growth patterns. As policymakers now advocate for a large-scale adoption of Transit-Oriented Development (DoHLGH and DoT 2023), and the planning for Dublin's first metro system, MetroLink, is now in its advanced stages (Department of Transport 2022), it is crucial that planners consider the unintended impacts of these initiatives, including the revealed effects on property prices. Concentrating on the less-affluent North Inner City offers policymakers a targeted insight, as more than three-quarters of the zones designated for TOD in the city are in disadvantaged areas (DoHLGH and DoT 2023)

Future research could explore the disamenity effects of close proximity to Luas stations, concentrating on the potential negative externalities, whether perceived or realised. In addition, further studies may investigate whether the property price premiums in certain areas led to the displacement of lower-income residents, exploring the dynamics of transit-induced gentrification and the related socio-economic implications. This would provide critical insight for policymakers in Ireland considering TOD and the MetroLink system, which also extends into the northside of the city (Department of Transport 2022).

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Appendix

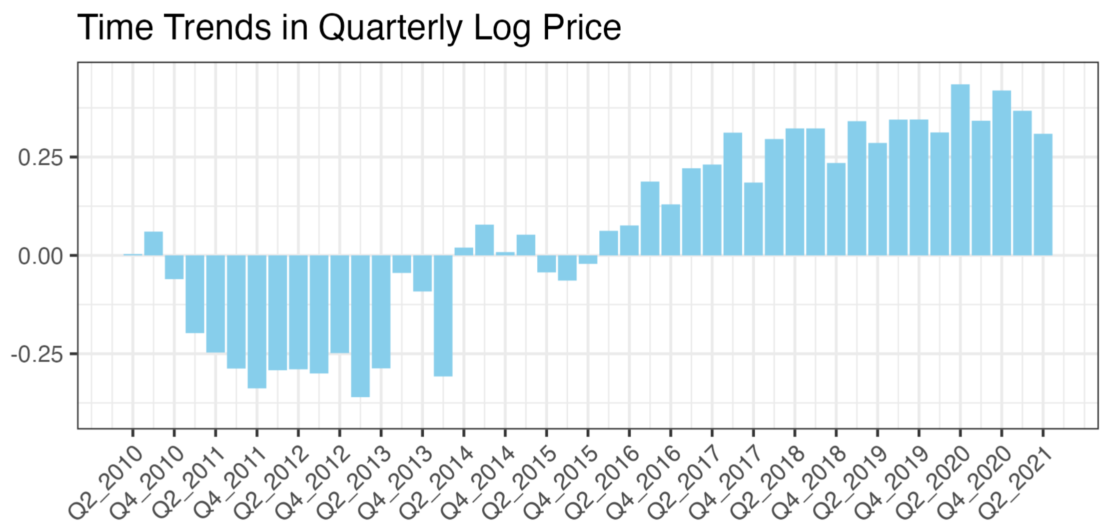

Figure A1: Time Trends Model

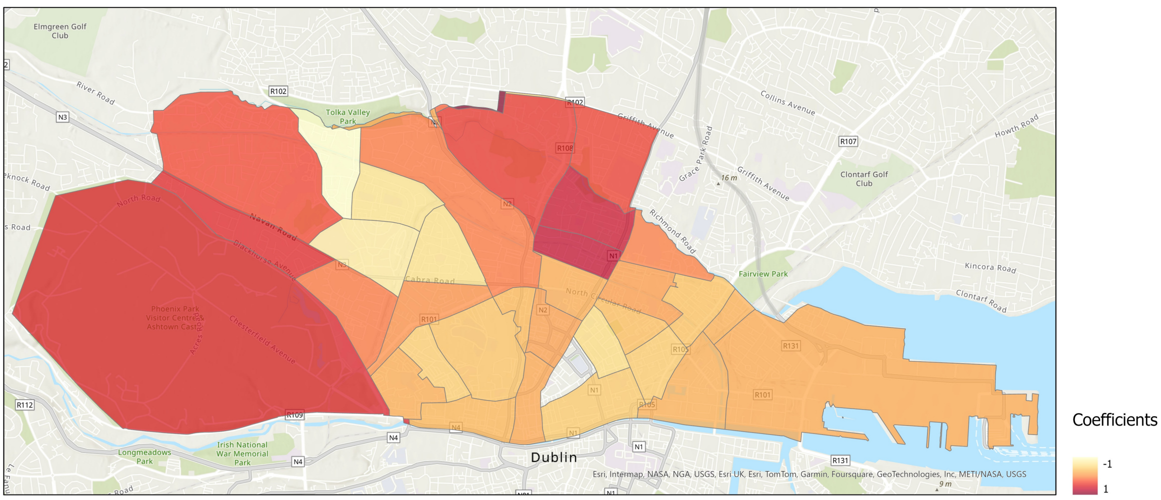

Figure A2: Location Trends Model

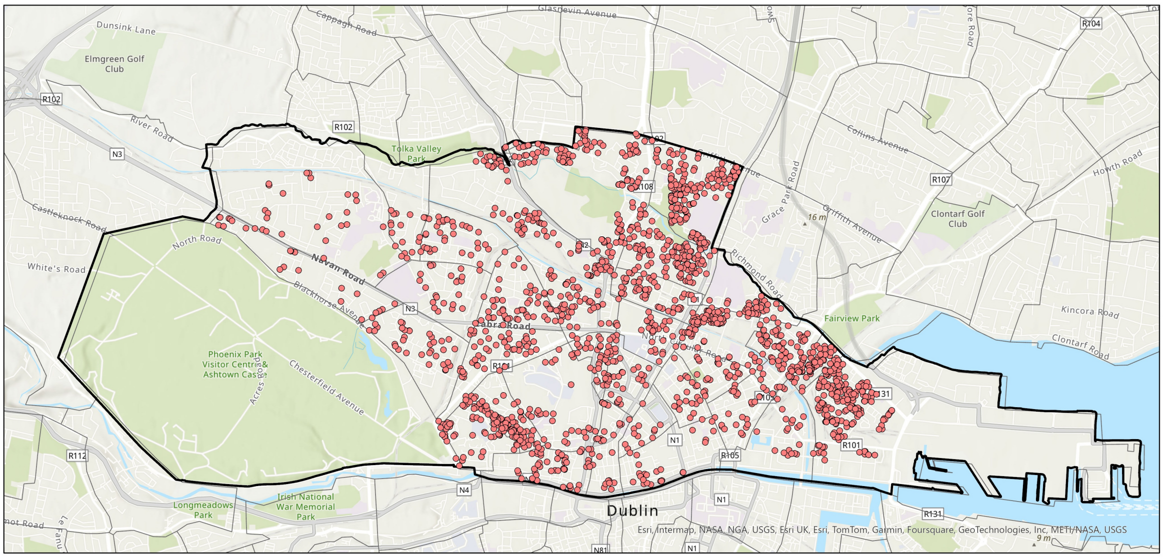

Figure A3: Properties in Dublin City Council Central Area