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House price discontinuity at the border: Evidence from Luxembourg and its neighbouring regions*

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Abstract

This paper estimates the discontinuity in house prices at Luxembourg’s border with its three neighbouring countries, Belgium, France and Germany. We use propensity score matching techniques and representative survey data on house valuations by households living in Luxembourg or its surrounding regions. Using a sample of properties close to the border, we find a large quality-adjusted Luxembourg housing premium, with substantial heterogeneity by border segment. Property prices on the Luxembourg side of the border are 35% higher than on the German side, and 111%-112% higher than on the French and Belgian sides. Prices on the Luxembourg side are similar along all three border segments, implying that the heterogeneity in the estimated discontinuities mainly reflects differences in prices on the neighbouring-country side, which may in turn reflect both national institutional differences and local market conditions. Overall, the estimated discontinuities persist after controlling for intrinsic property characteristics and key geographical determinants.

Keywords: Property prices, cross-border, border discontinuity, housing policies; housing wealth.

JEL classifications: R31; R32; R23; J61.

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Résumé non technique

Les prix des logements au Luxembourg sont nettement supérieurs à ceux observés dans les régions voisines de Belgique, de France et d'Allemagne. Cet article analyse les prix de logements comparables de chaque côté de la frontière à partir de deux enquêtes harmonisées menées en 2021 : l'enquête luxembourgeoise sur le comportement financier et de consommation, qui couvre les ménages résidant au Luxembourg, et une enquête correspondante, qui couvre les ménages frontaliers, qui vivent dans les régions voisines, bien qu'au moins un membre travaille au Luxembourg. Les deux enquêtes contiennent des informations détaillées sur la résidence principale, notamment sa valeur telle qu'estimée par le propriétaire-occupant, sa taille, son type (appartement ou maison), sa période de construction et sa localisation.

Afin de réduire les différences liées à la localisation, l'article se concentre sur les logements situés dans une bande étroite de part et d'autre de la frontière luxembourgeoise et compare des logements présentant des caractéristiques observables similaires. Les principales méthodes utilisées sont un modèle de prix hédonique et l'appariement par score de propension. L'analyse tient compte de la taille du logement, de son âge, de son type, de la distance par rapport au centre de Luxembourg-ville et de la frontière concernée.

Les résultats mettent en évidence une forte prime immobilière au Luxembourg, même à proximité immédiate de la frontière. Cette prime est la plus élevée le long des frontières avec la Belgique et la France : après ajustement en fonction des caractéristiques observables, y compris la localisation, les logements situés du côté luxembourgeois sont estimés environ 112 % plus chers que les logements comparables situés du côté belge et environ 111 % plus chers que les logements comparables situés du côté français. Le long de la frontière allemande, la prime est plus faible mais demeure importante à environ 35 %. Ces résultats sont robustes à l'utilisation de bandes plus étroites ou plus larges autour de la frontière ainsi qu'à des formes alternatives d'appariement. La discontinuité renvoie probablement à des différences dans la structure des marchés du logement, l'accessibilité et les conditions locales de demande.

Même dans un marché de travail fortement intégré comme celui de la Grande Région, les frontières nationales jouent un rôle important sur le marché du logement. Les différences en matière de fiscalité, de politiques du logement, de prestations sociales, de réglementation, de conditions économiques locales et de contraintes d'offre de logements peuvent toutes contribuer aux écarts de prix observés. Les résultats sont donc pertinents pour comprendre l'accessibilité au logement au Luxembourg, l'installation de ménages dans les régions voisines, ainsi que le rôle plus large des politiques nationales dans la formation des marchés locaux du logement.

Nicht-technische Zusammenfassung

Die Immobilienpreise in Luxemburg liegen deutlich über denen in den benachbarten Regionen Belgiens, Frankreichs und Deutschlands. Der vorliegende Artikel untersucht, ob ähnliche Wohnimmobilien, die nahe beieinander liegen, sich jedoch auf beiden Seiten der luxemburgischen Grenze befinden, deutlich unterschiedliche Werte aufweisen.

Die Analyse stützt sich auf zwei harmonisierte Haushaltserhebungen aus dem Jahr 2021: die luxemburgische Erhebung zum Finanz- und Konsumverhalten der Haushalte, die in Luxemburg ansässige Haushalte erfasst, und eine entsprechende Erhebung, die Grenzgängerhaushalte in den Nachbarregionen erfasst, bei denen mindestens ein Mitglied in Luxemburg arbeitet. Beide Erhebungen enthalten detaillierte Informationen zum Hauptwohnsitz der Haushalte, insbesondere zu dessen von den Eigentümern geschätztem Wert, seiner Größe, seiner Art (Wohnung oder Haus), seinem Baujahr und seiner Lage.

Um Unterschiede hinsichtlich der Lage zu verringern, konzentriert sich der Artikel auf Immobilien, die in einem schmalen Streifen beiderseits der luxemburgischen Grenze liegen, und vergleicht Immobilien mit ähnlichen beobachtbaren Merkmalen. Die wichtigsten verwendeten Methoden sind ein hedonisches Preismodell und das Propensity-Score-Matching. Die Analyse berücksichtigt die Größe, das Alter, den Typ der Immobilie sowie die Entfernung zum Stadtzentrum von Luxemburg und zur betreffenden Grenze.

Die Ergebnisse zeigen einen starken Preisaufschlag für Wohnimmobilien in Luxemburg, selbst in unmittelbarer Grenznähe. Nach Bereinigung um beobachtbare Merkmale (einschließlich der Lage) sind Immobilien auf der luxemburgischen Seite schätzungsweise 112% teurer als vergleichbare Immobilien auf der belgischen Seite und 111% teurer als vergleichbare Immobilien auf der französischen Seite. Entlang der deutschen Grenze ist der Aufschlag mit rund 35% geringer, aber immer noch beträchtlich. Diese Ergebnisse sind robust gegenüber der Verwendung von engeren oder breiteren Entfernungsbereichen rund um die Grenze herum sowie gegenüber verschiedenen Matching-Spezifikationen. Die Diskontinuität ist vermutlich auf unterschiedliche Strukturen des Wohnungsmarktes, Erreichbarkeit und lokale Nachfragebedingungen zurückzuführen.

Selbst auf einem stark integrierten Arbeitsmarkt wie dem der Großregion spielen nationale Grenzen auf dem Wohnungsmarkt eine wichtige Rolle. Unterschiede in der Besteuerung, der Wohnungspolitik, den Sozialleistungen, der Regulierung, den lokalen wirtschaftlichen Bedingungen und Engpässen beim Wohnungsangebot können alle zu den beobachteten Preisunterschieden beitragen. Die Ergebnisse sind daher relevant für das Verständnis der Er-schwinglichkeit von Wohnraum in Luxemburg, der Abwanderung von Haushalten in benachbarte Regionen sowie der umfassenderen Rolle nationaler politischer Rahmenbedingungen bei der Gestaltung lokaler Wohnungsmärkte.

Non-Technical Summary

Property prices in Luxembourg are significantly higher than those observed in neighbouring regions of Belgium, France and Germany. This article examines whether similar properties, situated close to one another but on either side of the Luxembourg border, have significantly different values.

The analysis uses two harmonised household surveys conducted in 2021: the Luxembourg Household Finance and Consumption Survey, covering households residing in Luxembourg, and a corresponding survey covering households residing in neighbouring regions with at least one member working in Luxembourg. Both surveys contain detailed information on households' main residence, including its value as estimated by homeowners themselves, its size, type (apartment or house), year of construction and location.

To reduce differences linked to location, the paper focuses on properties situated within a narrow strip on either side of the Luxembourg border and compares properties with similar observable characteristics. The main methods used are a hedonic price model and propensity score matching. The analysis takes into account the size of the property, its age, its type, the distance from Luxembourg city centre and the corresponding border.

The results highlight a significant property price premium in Luxembourg, even in the immediate vicinity of the border. This premium is highest along the borders with Belgium and France: after adjusting for observable characteristics, including location, properties on the Luxembourg side are estimated to be approximately 112% more expensive than comparable properties on the Belgian side and approximately 111% more expensive than comparable properties on the French side. The premium is lower, though still significant, along the German border, where it stands at around 35%. These results are robust to the use of narrower or wider distance bands around the border and to various matching specifications. The price discontinuity likely reflects differences in the structure of housing markets, accessibility, as well as local demand and supply conditions.

Even in a highly integrated labour market such as that of the Greater Region, national borders play an important role in the housing market. Differences in taxation, housing policies, social benefits, regulation, local economic conditions and housing supply constraints may all contribute to the observed price differentials. The findings are therefore relevant to understanding housing affordability in Luxembourg, the relocation of households to neighbouring regions, and the broader role of national policy frameworks in shaping local housing markets.

1 Introduction

Differences in institutional and regulatory environments—such as varying taxes and subsidies—segment markets and give rise to price and wage discontinuities at national borders.¹ This paper studies such discontinuities for properties along the border of Luxembourg with its neighbours Belgium, France and Germany.

Empirical studies, mainly in the urban and metropolitan context, show that geographical boundaries affect house prices. According to these studies, house prices can vary with access to public infrastructure, school rankings or crime records. For example, an invisible school district boundary can effectively determine access to schools with good reputation and ranking, driving up house prices in those areas (e.g. [Black, 1999](#); [Gibbons and Machin, 2003, 2006](#); [Bayer et al., 2007](#); [Fack and Grenet, 2010](#)). [Boustan \(2013\)](#) shows how the underlying house price premium between high- and low-income neighbourhoods is intrinsically related to lower property tax rates and better school quality. Districts with high crime rates suffer from lower demand, in turn depressing house prices (e.g. [Lynch and Rasmussen, 2001](#); [Gibbons, 2004](#); [Gibbons and Machin, 2008](#)). Similarly, evidence from China’s household registration system also suggests that locations with better access to welfare benefits, such as compulsory education, social insurance, minimum subsistence allowances and housing affordability benefits, have higher house prices (e.g. [Chen et al., 2019](#)).

However, the study of *international* borders and their effects on residential real estate markets remains relatively under-explored, particularly in the context of highly integrated cross-border labour markets within the European Union. Recent studies have begun to address this gap. [Micheli et al. \(2019\)](#), for example, analyse house price discontinuities at the Dutch-German border and show that properties on the Dutch side are around 15%-17% more expensive than comparable properties on the German side. [Kudashev and Picard \(2025\)](#) develop a quantitative urban economics model and use advertised price data scraped from a popular Luxembourg property listing website, including properties for sale and to let. They estimate that prices drop by around 60% when crossing the Luxembourg border to neighbouring countries.

Our paper contributes to the above literature by offering a detailed investigation of house price differences at the Luxembourg border.² Specifically, we divide the border into three distinct segments corresponding to its borders with Belgium, France, and Germany. This allows us to compare differences in prices across countries. This disaggregated approach reveals variations in border effects that cannot be addressed by aggregate analyses, providing deeper insights into localised economic and market conditions that shape house prices.

We compare the prices of similar properties (in terms of characteristics, such as size, construction year, and type) located near, but on opposite sides of, Luxembourg’s border. To do so, we use data on residential properties collected

¹The economic literature has extensively documented the effects of borders, for example, by highlighting their influence on trade volumes (e.g. [Anderson and Wincoop, 2003](#)) or price differences (e.g. [Engel and Rogers, 1996](#); [Messner et al., 2024](#)). Discontinuities generate arbitrage opportunities that, if large enough, are systematically exploited through cross-border shopping (e.g. [Asplund et al., 2007](#); [Manuszak and Moul, 2009](#); [Mathä et al., 2017](#)), commuting for work (e.g. [Coomes and Hoyt, 2008](#); [Agrawal and Hoyt, 2018](#)) or migration (e.g. [Stark, 1984](#); [Gabriel et al., 1993](#)).

²Throughout the paper, we use ‘house’ generically to refer to residential property, including the associated land.

through two household surveys conducted in 2021. These surveys contain data on households' main residences and their postcodes, allowing us to locate the properties and to calculate distances from the border or Luxembourg city centre. Importantly, both surveys contain homeowners' self-assessed valuations of their property, allowing us to analyse price differences for the residential property market as a whole, rather than just for properties that have been sold, are for sale or for rent. We employ various methodologies, including the hedonic price model (HPM) and matching methods, such as Propensity Score Matching (PSM) (with regression adjustment) or Multivariate Distance Matching. To minimise the influence of locational effects, we only compare the prices of houses located within a narrow strip on either side of the Luxembourg border.

Furthermore, a geographic regression discontinuity design (RDD) would require that, absent the jurisdictional boundary, potential property values vary smoothly at the border. In our setting, this continuity assumption is questionable because households can sort across the border and the composition of the housing stock itself differs between the two sides, a concern that is well established in studies of residential sorting around spatial boundaries (e.g. [Bayer et al., 2007](#)). Indeed, observable property characteristics such as type and age are not fully continuous at the boundary. We therefore use matching within a narrow border strip as our main empirical strategy, conditioning on observed property and location characteristics. The resulting estimates should be interpreted under a selection-on-observables assumption rather than as an RD-based causal effect of crossing the border.³

We start with the hedonic price models (HPM) and move on to propensity score matching (PSM) kernel methods with regression adjustment. Our primary estimates rely on propensity-score methods that explicitly account for differences in property characteristics within a narrow 4 kilometre strip and restrict inference to the region of common support. This method identifies a substantial quality-adjusted price premium in Luxembourg under selection-on-observables. In addition, our findings point to considerable heterogeneity in house price discontinuities across the three border segments. After adjusting for property characteristics and location determinants, our results suggest that house prices are 112%-116% higher on the Luxembourg side than on the Belgian side of the border, depending on the methodology used. The estimated effect at the France–Luxembourg border ranges between 111% and 123%. In contrast, the estimated effect of the Luxembourg–Germany border is lower, ranging between 35% and 56%. The varying price discontinuity is mainly linked to different property prices along the non-Luxembourg side of the three border segments, suggesting differences in the structure of housing markets, accessibility and local demand and supply conditions across bordering regions. The segment-specific estimates should therefore be interpreted as reduced-form border effects that combine national institutional differences with local geography and market structure. Overall, our results hold for different methodological approaches employed, which underscores the robustness of our findings.

The results of this paper are of interest for several reasons. Firstly, these pronounced discontinuities likely reflect

³For completeness, Appendix [A.2](#) reports RD estimates as a complementary robustness exercise. Because residential and housing-stock sorting may compromise continuity at the geographic boundary, we do not treat the RD specification as our preferred identification strategy.

differences in national policies, as well as localised economic and policy environments. Differences in labour income taxes and social security contributions coupled with varying legal, financial and administrative fees for buying, selling or owning property directly affect affordability and transaction costs in the four countries. In addition, the international border represents a geographic boundary for access to various employment-based social policies (e.g., tax allowances for commuting expenses, scope to work from home) and residence-based social policies (e.g., unemployment benefits, housing subsidies). In particular, mortgage subsidies for owner-occupied housing, property and capital income taxes (e.g., [Organisation of Economic Cooperation and Development, 2022](#); [Claveres et al., 2020](#)) differ markedly between the four countries and can, therefore, shift the demand for housing at different sides of the border. In the years leading up to the survey, Luxembourg’s strong economic growth and substantial net migration inflows had increased housing demand and contributed to rising house prices, while housing supply remained limited.

Secondly, the research question is relevant for other cross-border areas with functional urban areas spanning over different jurisdictions, such as various U.S. multi-state Metropolitan Statistical Areas (MSA). In the U.S., an estimated 75 million people live in multi-state MSAs (e.g., [Agrawal and Hoyt, 2018](#)). Similarly, in the EU, 34% of regions share a border with regions of other countries, accounting for 44% or 145 million of its total population ([Berzi et al., 2025](#)). 1.7 million people commute across national borders in the EU and EFTA countries ([Hassan et al., 2023](#)) and are therefore directly affected by policy discontinuities. Cross-border regions, such as Annecy-Geneva, Basel-Mulhouse-Freiburg or Copenhagen-Malmö directly spring to mind. In this context, measuring border discontinuities may help understand the effect of national borders on various economic outcomes and inform how national policies (e.g., quality of transport networks) affect employment and population locations.

Thirdly, for most households in Europe, owner-occupied housing is the most important asset. In Luxembourg and other European metropolitan areas, housing affordability is a major concern (e.g., [Cousin et al., 2025](#)). An increasing number of Luxembourg households relocate across the border to enjoy lower housing and living costs, while maintaining their jobs in Luxembourg.⁴ This growing trend is relevant in the context of research findings. [Borck et al. \(2010\)](#) demonstrate that reduced transport cost (e.g., commuting costs through investment in cross-border public infrastructures) can lead to increased spatial concentration of production and increased residential dispersion. [Parkhomenko \(2026\)](#) shows that cities may hollow out; they lose the middle-income households, who cannot afford homeownership and therefore relocate to cheaper locations, which in turn results in increased polarisation and income inequality.

The remainder of the paper is organised as follows: Section 2 provides a brief geographic context of the study, Section 3 presents the data and methodology. Section 4 discusses the empirical results. Section 5 concludes.

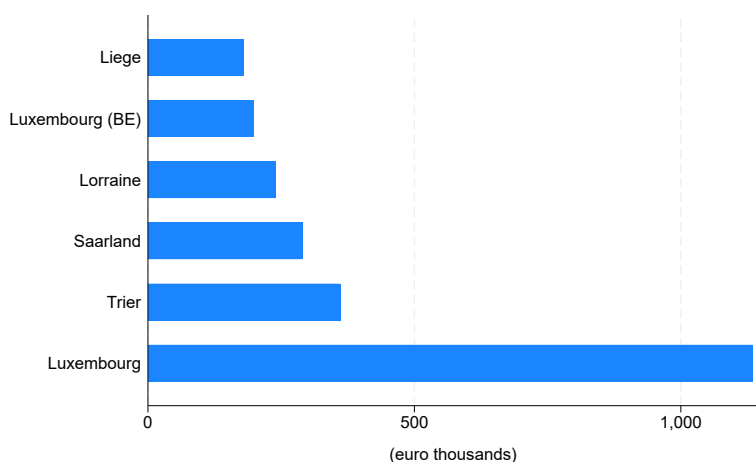
⁴See [Zanardelli \(2025\)](#) for recent figures. This trend has been discussed in the Luxembourg media and has also been raised in political debates ([Mennicken, 2025](#)). In 2018, over 90% of cross-border commuting households that had relocated outside of Luxembourg reported high house prices in Luxembourg as an important factor for their (re-)location decision (e.g., [Chen et al., 2021](#)).

2 Geographic context - A brief description

Our study focuses on the “Greater Region”, a cross-border area that includes the country of Luxembourg at its centre, the regions Wallonia (Belgium) in the west, Lorraine (France) in the south and Rhineland-Palatinate and Saarland (both Germany) in the east. The Luxembourg border with Belgium spans 148 kilometres (92 miles), the border with France 73 kilometres (45 miles) and the border with Germany 138 kilometres (86 miles).

Property prices in Luxembourg are significantly higher and have grown faster than those in neighbouring regions. As depicted in Figure 1, in the fourth quarter of 2021, the average price for any type of property located in Luxembourg was on average more than three times as high as that in any other neighbouring region (at the NUTS 2 level). These exceptionally high prices are the result of a prolonged upward trajectory that continued until 2022, with nominal price increases of 118% between 2012 and 2022, compared to 44% in the euro area (European Commission, 2023). See Figure 2 for a comparison of the evolution of real estate prices in Luxembourg and the neighbouring countries at the regional level.⁵

Figure 1: Property prices in Luxembourg and neighbouring regions

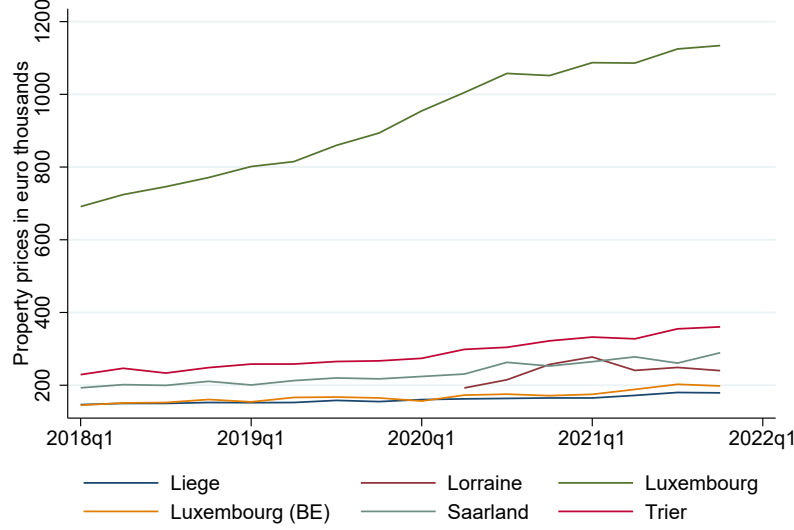


Note: Average prices for any type of property in the region disaggregated at NUTS2 level for the 4th quarter of 2021. For Germany, France and Luxembourg the series correspond to advertised prices on real estate websites retrieved by Koetter and Noth (2022) and Luxembourg’s L’Observatoire de l’habitat - Ministère du Logement. For Belgium only transaction prices are available at the NUTS2 disaggregation level. Data were retrieved from Statbel, the Belgian statistics office.

This surge in property prices in Luxembourg stems largely from an influx of foreigners into the Luxembourg labour market in combination with relatively inelastic supply, which relies on attracting international talent as well as its integration within the Greater Region. The country’s strong economy and its status as a financial hub in Europe attract many international businesses, sustaining labour demand and attracting migrant workers and cross-border commuters, who live in neighbouring countries but work in Luxembourg. According to the 2021 census

⁵Evidence of house price differences between Luxembourg and the neighbouring regions are also reported in the geography profession (e.g., Diop, 2011).

Figure 2: Evolution of property prices in Luxembourg and neighbouring regions



Note: See Note in Figure 1

data, Luxembourg counted approximately 280,000 resident workers, of whom 59% were born abroad. Furthermore, cross-border commuters accounted for around 46% of total employment in Luxembourg. Despite its small size—a population of around 644,000 and a geographical area of 2,586 km²—Luxembourg has the highest number of cross-border commuters in the European Union. More than 220,000 people commute from Belgium (25%), France (50%) and Germany (25%) to Luxembourg. Most cross-border commuters live in a small area close to the Luxembourg border. They accept longer daily travel times on average (i.e., 45-54 minutes on average, depending on their country of origin) compared to employed residents (i.e., 26 minutes on average) (Mathä et al., 2024), and thus higher transport costs, in exchange for higher wages in Luxembourg and lower living costs in their country of residence.

3 Data and Methodology

3.1 Empirical strategy

We estimate the size of the house price discontinuity (expressed in logarithmic terms) using the hedonic pricing model and propensity score matching techniques. Matching within a small strip from the border (e.g., 4 km) and then applying local estimation ensures that the properties are very similar in terms of observable characteristics, while restricting the analysis to a similar surrounding area. This hybrid approach better isolates the border effect by minimising the influence of spatial heterogeneity. A similar approach was employed by Liu et al. (2024) in a hedonic valuation of green amenities, using a spatial piecewise matching algorithm that minimises differences in housing

characteristics between properties with different levels of green space. In a similar fashion, Papadogeorgou et al. (2018) augment propensity-score matching with a spatial distance penalty to preserve both covariate balance and geographic proximity—a core feature of localised matching designs. Although they focus on the impact of coal mines on house prices, Fitzpatrick and Parmeter (2021) show how matching followed by local modelling within distance thresholds (e.g., around natural resource sites) can produce transparent spatial effects. Their approach, which is based on nearest-neighbour covariate matching with distance-based local regressions, can be transferred to other contexts. They actively match homes based on proximity to mines and covariates, and then estimate local linear models within distance bins to trace spatial decay effects.

To clarify the empirical approach, consider the standard hedonic model for property prices. In this framework, the logarithm of the market value ($Price_{ij}$) of a representative property i in a location j is expressed as a function of the property’s observable attributes (X_i), other environmental characteristics (G_j), and an error term (u_{ij}).

$$Y_{ij} = \log(Price_{ij}) = f(X_i, G_j, B_i, u_{ij}) \quad (1)$$

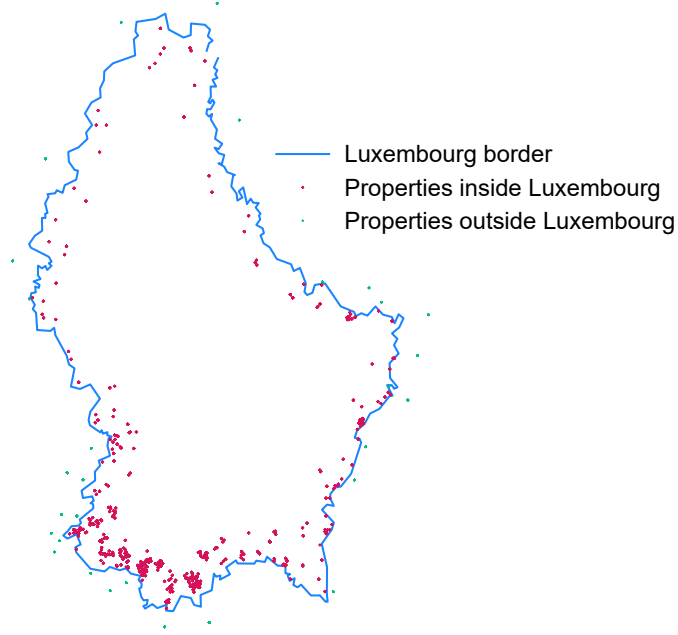
Our objective is to estimate differences in residential property prices across the Luxembourg border. We capture this difference with a variable B_i , indicating whether the property is located in Luxembourg or in Belgium, France or Germany. If relevant determinants of property prices are omitted and correlated with location on either side of the border, the estimated border effect may be biased, i.e. $cov(B_i, u_{ij}) \neq 0$. To limit the influence of spatial heterogeneity, we restrict the analysis to properties located within a narrow strip on either side of the Luxembourg border. Specifically, we compare properties located inside Luxembourg at a maximum distance S from the border (*treated area* A^t) with properties located within the same maximum distance S outside Luxembourg (*control area* A^c). Figure 3 illustrates these areas for $S = 4$ km. Restricting the sample in this way ensures that properties from the treated and control group are drawn from geographically localised areas around the same national border, thereby reducing, although not eliminating, differences in location-specific factors. The subsequent matching procedure further improves comparability by balancing observed property and location characteristics, including distance to Luxembourg city centre and the relevant border segment.

To calculate the distance to the border for each property we must first define a finite number of points along the border ($b = 1, 2, \dots, 273$)⁶. We then use the Haversine formula to calculate the great-circle distance for each property location based on the postcode provided by participating households in the HFC surveys.⁷ We select the closest border point for every single property in the two surveys. If a property is located between a distance of S km outside and S km inside the border, it is classified as either a *control area* (A^c) or a *treated area* (A^t).

⁶Based on the SAS® Visual Analytics geo map for Luxembourg, 273 points were used.

⁷Luxembourg employs a highly granular postcode system: in smaller municipalities, a single code typically encompasses the entire settlement, whereas in Luxembourg City, individual streets are generally assigned distinct codes. For extended streets, the allocation may be further subdivided into multiple codes to enhance locational specificity.

Figure 3: Properties close to the border (4 km) by postcode



Selecting properties with similar characteristics reduces the possibility of omitted variable bias in the border effect estimate. For this reason we use a statistical matching approach (Propensity Score Matching or Mahalanobis Distance Matching) to select properties within the *treated area* (A^t) for the treated sample (i.e. those located in Luxembourg), as well as properties from the *control area* (A^c) for the control sample based on a set of matching attributes (X_i).⁸ These attributes include the property size, age (year 2021 minus the construction year), type (e.g. house or apartment⁹), and distance to the Luxembourg city centre.¹⁰ Dichotomous variables were also included to represent the three separate border segments based on the country closest to the property: Belgium (used as the base category), France or Germany.

This method uses a standard discrete choice parametric model to predict the likelihood that a property in location j lies within Luxembourg's borders ($B_i = 1$), given a set of observable characteristics or attributes (X_i) among properties and locations: in the *control* (A^c) and *treated areas* (A^t).

$$\Pr(B_i = 1 \mid X_i, G_j) = \pi(X_i, G_j), \quad (2)$$

⁸Since the assignment of the treatment (being inside the border) is not determined at random, it is questionable whether a regression discontinuity design (RDD) is appropriate in our setting. The Luxembourg border does not function as an exogenous cut-off point that selects randomly properties into treated and non-treated units. This is as households intentionally choose on which side to live, taking into account differences in prices, size, amenities and regulations. Because households sort across the national border and property characteristics may differ discontinuously between the two sides, the continuity assumption required for a causal geographic RD interpretation may not hold (see Butts, 2023).

⁹Other types of properties such as farms or rental housing are excluded from both treatment and control groups.

¹⁰We use the coordinates of the main square in Luxembourg City - *la Place d'Armes* - as the central point.

where $\pi(X_i, G_j)$ is the propensity score, such that the average treatment effect can be estimated by conditioning on the propensity score rather than X . Let Y_{ij}^1 denote the potential outcomes (log-prices) if the property is in the treatment area (inside Luxembourg) and Y_{ij}^0 if it is in the control area (outside Luxembourg). The conditional independence assumption can then be written as follows:

$$(Y_{ij}^0, Y_{ij}^1) \perp B_i \mid X_{ij}, G_j. \quad (3)$$

This means that, given the property characteristics and location, whether a property is inside Luxembourg is independent of its potential outcomes. As we are only comparing properties within a narrow strip close to the border (within a distance of S km), the location-specific effect G_j is approximately the same for matched treated and control properties. Restricting the analysis to a narrow border strip reduces geographical heterogeneity but does not eliminate it. We therefore condition on observed property and location characteristics, including distance to Luxembourg City and the relevant border segment, when implementing the matching procedure.

For estimates using propensity score matching, the average treatment effect (ATE) is calculated for the sample of treated and control groups over the common support, after weighting the observations using the propensity score distribution of participants (Caliendo and Kopeinig, 2008). The Average Treatment on the Treated (ATT) is defined as:

$$ATT = \frac{1}{N^T} \sum_{i \in T} (Y_{ij} - \hat{Y}_{ij}^0), \quad \hat{Y}_{ij}^0 = \sum_{k \in C} w_{ik} Y_{kj}, \quad (4)$$

The Average Treatment on the Control (ATC) is defined as:

$$ATC = \frac{1}{N^C} \sum_{i \in C} (\hat{Y}_{ij}^1 - Y_{ij}), \quad \hat{Y}_{ij}^1 = \sum_{k \in T} w_{ik} Y_{kj}, \quad (5)$$

Different matching algorithms use different definitions of the matching weights, $w_{i,k}$. In particular, kernel matching involves matching each treated observation with several control observations, with weights that decrease with the distance between propensity scores.¹¹

The Average Treatment Effect (ATE) is the sample-share weighted average of the ATT and ATC:

$$ATE = \left(\frac{N_T}{N} \cdot ATT \right) + \left(\frac{N_C}{N} \cdot ATC \right), \quad (6)$$

¹¹The weights are defined as follows: $w_{ik} = \frac{K\left(\frac{\pi(X_{kj}) - \pi(X_{ij})}{h}\right)}{\sum_{k \in C} K\left(\frac{\pi(X_{kj}) - \pi(X_{ij})}{h}\right)}$, where h is a bandwidth parameter, $K(\cdot)$ is the kernel function assigning higher weight to control properties $k \in C$ whose propensity scores $\pi(X_{kj})$ are closer to the treated property i 's score $\pi(X_{ij})$, and the denominator normalizes the weights so that they sum to one across all matched controls for property i .

where $N = N_T + N_C$ denotes the number of treated and control observations in the matched sample over common support. Substituting the definitions of the ATT and ATC into the previous expression, the ATE can be written as:

$$ATE = \frac{1}{N} \left(\sum_{i \in T} Y_{ij} - \sum_{i \in T} \sum_{k \in C} w_{ik}^0 Y_{kj} \right) + \frac{1}{N} \left(\sum_{i \in C} \sum_{k \in T} w_{ik}^1 Y_{kj} - \sum_{i \in C} Y_{ij} \right). \quad (7)$$

Here, w_{ik}^0 denotes the matching weight used to construct the counterfactual outcome for treated property i from comparable control properties k , while w_{ik}^1 denotes the matching weight used to construct the counterfactual outcome for control property i from comparable treated properties k . This expression separates the two components of the ATE. The first term in parentheses is the contribution of treated properties, comparing their observed log prices inside Luxembourg with the matched counterfactual log prices they would have had outside Luxembourg. The second term in parentheses is the contribution of control properties, comparing their matched counterfactual log prices inside Luxembourg with their observed log prices outside Luxembourg. In both cases, the weighted sums over matched observations approximate the relevant counterfactual outcomes.

The estimated ATE can therefore be interpreted as the average quality-adjusted log-price differential between properties located within the treatment area A^t inside Luxembourg and comparable properties located within the control area A^c outside Luxembourg, within the selected border strip of S kilometres and over the region of common support. Unlike the ATT, the ATE is not restricted to the distribution of characteristics of treated properties only; it combines the treatment and control components according to their relative shares in the matched sample.

While these methods offer a useful approximation of counterfactuals, the border design still has several limitations that could impact the precision and interpretation of the estimated effects. Firstly, propensity score matching (PSM) only balances observed characteristics (X_{ij}), leaving unobserved factors such as household preferences or property quality as potential sources of bias. To test for the possibility that we are not measuring the effect of unobserved property-related factors, we conduct a placebo test by introducing spurious borders, shifting the Luxembourg border to locations where no actual jurisdictional change occurs, and re-running the matching and estimation procedures. If no significant effects are observed at these placebo borders, this provides evidence that the original border effect is unlikely to be driven by unobserved household characteristics or property quality. This addresses concerns about these potential sources of bias (Guo and Minier, 2021; Berta et al., 2024). Secondly, location-specific effects (G_j) may still vary within the chosen distance S , and the arbitrary choice of S can affect the results by either reducing the sample size or introducing heterogeneity. We therefore include additional geographic controls, such as specific border segments, and conduct sensitivity analyses using multiple S values (e.g., 3, 4, 5 km) in the robustness checks section. Thirdly, poor overlap or extreme weights can make matching less reliable, and the choice of kernel and bandwidth (h) can influence the estimated effects. We mitigate this by trimming the sample to common support, i.e., by removing properties with propensity scores outside the overlapping range, and through the use of alternative

matching algorithms (e.g., nearest neighbour and Mahalanobis distance). The results are compared in the appendix. Finally, border effect estimations may capture policy differences that are not directly controlled for, which remains a potential limitation of this design. Overall, combining PSM with regression adjustment, high-resolution geographic controls, and robustness checks enables us to provide estimates that capture the price differential while minimising bias from observable and location-specific factors.

3.2 Data description

We use data from two household surveys. The Luxembourg Household Finance and Consumption Survey (LU-HFCS) collects household balance-sheet information from households residing in Luxembourg. The Cross-border Household Finance and Consumption Survey (XB-HFCS) collects the same information from cross-border commuter households, defined as households residing in the Greater Region with at least one member working in Luxembourg. Both surveys were conducted in 2021 by the Central Bank of Luxembourg and the Luxembourg Institute of Socio-Economic Research (LISER).

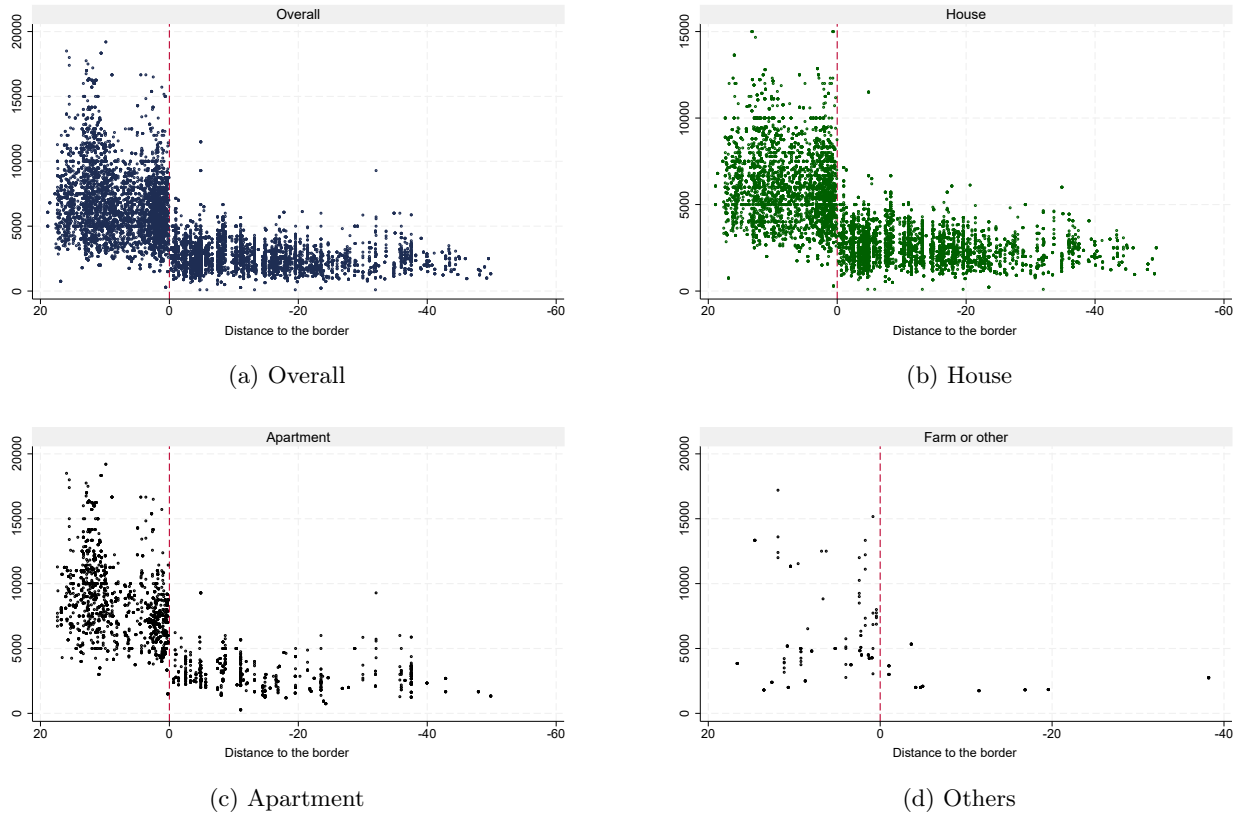
The two surveys are fully harmonised. They use the same questionnaire and survey mode, i.e. Computer Assisted Web-based Interviews (CAWI), and were conducted simultaneously between October and December 2021. They were jointly edited and multiply imputed using five imputates; approximately 6% of item responses were imputed to account for missing information. Estimates and standard errors are combined across the five imputates following Rubin’s rules. See [Mathä et al. \(2023, 2024\)](#) for detailed information on both surveys.

To measure property values, we rely on homeowners’ self-assessment of the value of their household main residence.¹² To ensure the same use (i.e. owner-occupied housing) for all properties and to minimise measurement error in self-assessed values, we exclude households renting their primary residence. This approach is consistent with [Naidin et al. \(2025\)](#), who find that homeowners’ assessments are, on average, only slightly higher than values imputed from observable market data. Renters, by contrast, are more prone to underreporting their home’s market value and are less likely to provide estimates that are in line with predictions from the hedonic model.

Figure 4a plots the value of the main household residence (HMR) in euro per square metre against its distance to the nearest border. A simple inspection reveals the discontinuity in prices between properties inside and outside the Luxembourg border. Not only does the average price increase when crossing the border into Luxembourg, but the price per square metre also varies more. The pattern is also visible when the sample is disaggregated by property type. This is not related to the property type. Breaking down the figure into categories such as houses, apartments

¹²Homeowners were asked “What is the value of this property, i.e. if you could sell it now how much do you think would be the price of it?”. [Mathä et al. \(2023\)](#) compare LU-HFCS self-assessed values with advertised prices from the “Observatoire de l’Habitat” and transaction prices from the “Administration de l’enregistrement, des domaines et de la TVA” (AED). For 2021, self-assessed values are reasonably close to AED transaction-price benchmarks, although differences remain across property types and the underlying price distributions are dispersed; advertised prices can differ more substantially. This evidence suggests that homeowners’ assessments provide a reasonable measure of residential property values, while not constituting transaction-price observations. Importantly for the cross-border comparison, property values are elicited using the same question and survey methodology in the LU-HFCS and XB-HFCS.

Figure 4: Value of main residence per square metre and distance to Luxembourg's border by property type



and others does not change the overall picture.¹³

Table 1 presents the mean prices for properties inside and outside the border, excluding those occupied by renters, and other types of property (OREPs and farms). Two additional columns present the mean price for a subset of properties close to the border (maximum distance of 4 km). Considering the overall sample, the average price of a property in Luxembourg is 2.6 times as high as that in neighbouring regions. Within the subset of properties close to the border, this ratio reduces to 2.0. Considering the geographic location significantly reduces the observed price differences. Nevertheless, the heterogeneity in the property characteristics, such as differences in their type (e.g. houses versus apartments), is still not accounted for. Houses are the most common type of main residence in our sample. Table 1 shows that 72% of Luxembourg homeowners in our sample own houses and 28% own apartments. By contrast, outside of the border, 89% of homeowners own houses and 11% own apartments. Considering all property types, the average property size is similar for the mean and median. In our sample, properties in Luxembourg are on average 4 years younger than those across the border.

¹³Given the very low number of observations available, we will exclude properties other than houses or apartments from the empirical analysis.

Table 1: Descriptive statistics by location

	(1) Inside Luxembourg Full sample	(2) Outside Luxembourg Full sample	(3) 4 km inside border	(4) 4 km outside border	(5) Test (4) - (3)
Mean					
Property price (Thousands)	1091.8 (16.0)	422.2 (5.0)	943.6 (26.4)	467.4 (14.3)	-12.3***
Property size	171.5 (2.2)	171.1 (1.8)	165.8 (3.6)	167.8 (4.2)	0.3
Property age	38.3 (1.0)	42.5 (1.2)	41.3 (1.7)	36.7 (2.5)	-1.5
Distance to city (Road)	19.5 (0.4)	54.1 (0.8)	26.3 (0.5)	36.7 (1.1)	9.5 ***
Median					
Property price (Thousands)	986 (15.0)	400 (6.0)	850 (20.9)	428 (17.2)	-12.7***
Property size	160.0 (3.1)	160 (2.1)	150 (4.5)	160 (4.7)	1.4
Property age	27 (1.1)	24 (1.3)	29 (1.7)	20 (1.9)	-3.2***
Distance to city (Road)	17.8 (0.3)	46.0 (0.5)	22.5 (0.6)	31.7 (0.8)	9.8***
Percentage(%)					
House	72.3 (1.1)	88.6 (0.7)	74.6 (1.8)	89.5 (0.9)	141.2***
Apartment	27.7 (1.2)	11.4 (0.7)	25.4 (1.8)	10.5 (0.9)	
Observations					
Minimum	1,455	1,599	537	253	
Maximum	1,458	1,600	548	259	

Notes: Standard errors are presented in parentheses. Column (1) corresponds to the sample encompassing all observations within Luxembourg. Column (2) encompasses all observations outside Luxembourg. Column (3) refers to the observations located within 4 kilometres inside the Luxembourg border. Column (4) shows the observations located within 4 kilometres outside the Luxembourg border. Column (5) reports t-statistics from a two-sided test and a Pearson's chi-squared test for categorical variables. Excludes other types of real estate property owned by the household to ensure a homogeneous Property use (other than housing). As the number of observations can vary across implicates, we report the minimum and maximum number of observations. The reported observations might come from different implicates.

In addition, Table 1 displays the descriptive statistics of properties located within 4 kilometres of either side of the border, distinguishing between those owned by Luxembourg resident and cross-border commuter households. In this narrow strip around the border, a higher proportion of cross-border commuter households own houses than Luxembourg residents (almost 90% versus 75%). The mean size and age of properties in this subset are remarkably similar. There is no statistically significant difference in mean age. However, with an average age difference of 9 years, the median age of properties in Luxembourg is significantly higher than that of properties outside Luxembourg.

An important factor in explaining house prices is geographic location and distance from the main centre of attraction. As many relevant employers in the region are located in Luxembourg, proximity to its central business district (CBD) is an important explanatory factor (Glumac et al., 2019). We calculate the distance to the Luxembourg

city centre using both the Haversine formula and road distance using OpenStreetMap.¹⁴ The median road distance between the city centre and properties located outside the border area is 46 kilometres, while for properties inside Luxembourg it is only 18 kilometres (see Table 1). When we focus on properties close to the border (within 4 kilometres on either side), their distance to Luxembourg city centre is naturally more similar. When using the road distance measure, the computed difference between properties inside and outside the border is around 10 kilometres (at the mean and median in Table 1). However, variability exists in accessibility and road quality connecting both properties inside and outside the border to Luxembourg’s city centre.

Apartments in Luxembourg are notably more expensive, with an average price of around €790k compared to just €280k outside. This premium persists even within a narrow 4 km strip from the border. Inside Luxembourg, the average price is €605k, while on the other side of the border it is €261k (Table 2). Apartments inside Luxembourg are somewhat smaller in size (91 m² vs 96 m²), while they are slightly larger within the 4 km strip (87 m² vs 83 m²). However, with an average age of 24 years, apartments in Luxembourg are significantly newer than those on the other side of the border, which are, on average, 42 years old. Within the 4 km strip, apartment ages are more similar, at 24 years inside the border and 28 years outside. Naturally, the average distance to Luxembourg city centre is lower for apartments inside the border (15 km overall, 25 km for properties on the inside strip) than for those outside the border (48 km overall, 27 km for properties on the outside strip). These contrasts emphasise the spatial premium and urban-centric development of apartments within Luxembourg.

The pattern is similar, but more pronounced, for houses. In 2021, the average cost of a house in Luxembourg was €1.21 million, compared to €441k outside the country. Within a 4 km distance from the border, prices remained higher (€1.06m vs €492k). In terms of size and age, Luxembourg houses are on average larger (202 m² vs 181 m²), and slightly older (44 years vs 42.5 years). However, houses just inside the border are on average substantially older (47 years) than those just outside the border (38 years). The distance differences are stark: the road distance to Luxembourg city centre is 27 km for houses inside the border, while it is 38 km for houses outside the border. This highlights Luxembourg’s suburban residential pattern of larger, pricier properties that are closer to the central business district than properties in neighbouring areas.

The regional housing market displays a pronounced border effect: properties located in Luxembourg are significantly more expensive, with average prices exceeding €1m compared to €374k–506k outside (Table 3). This aligns with broader findings that house prices in Luxembourg have surged substantially, doubling in real terms over the past decade, while prices in neighbouring markets, though growing, remain considerably lower. Even within a narrow 4 km strip around the border, substantial average price differences of €523k, €318k and €530k persist vis-à-vis Belgium, Germany and France, highlighting the strong spatial discontinuity in house prices when crossing the border.

¹⁴Road distance can be calculated using the OpenStreetMap API online service, which accepts origin and destination inputs and provides travel distance and duration for each combination. You can access a tutorial that walks you through the entire process using Python and the OpenStreetMap API at <https://github.com/gpulina/GPS-Distance-Duration>.

Table 2: Mean by Property type

	(1)	(2)	(3)	(4)
Mean	Inside Luxembourg Full sample	Outside Luxembourg Full sample	4 km inside border	4 km outside border
<i>Apartments</i>				
Property price (thousands)	790.0 (21.8)	280.4 (10.8)	604.7 (21.8)	261.0 (18.9)
Property size	91.3 (1.5)	95.6 (2.5)	87.5 (2.3)	83.4 (4.6)
Property age	23.6 (1.2)	42.3 (2.8)	23.9 (2.1)	28.0 (5.5)
Distance to city (Haversine)	11.4 (0.5)	37.9 (1.3)	19.6 (0.7)	21.7 (0.8)
Distance to city (Road)	15.1 (0.7)	47.8 (1.7)	25.3 (1.0)	27.4 (1.3)
Observations				
Minimum	402	182	135	26
Maximum	405	183	139	28
<i>Houses</i>				
Property price (thousands)	1,207.5 (19.7)	440.5 (5.3)	1,058.7 (32.3)	491.5 (14.9)
Property size	202.2 (2.4)	180.8 (1.8)	192.4 (3.9)	177.7 (4.1)
Property age	44.0 (1.3)	42.5 (1.3)	47.2 (2.1)	37.7 (2.7)
Distance to city (Haversine)	15.5 (0.3)	41.7 (0.6)	19.9 (0.5)	28.0 (0.8)
Distance to city (Road)	21.2 (0.5)	54.9 (0.8)	26.6 (0.6)	37.8 (1.2)
Observations				
Minimum	1051	1416	402	226
Maximum	1054	1418	409	232

Notes: Standard errors are presented in parentheses. Column (1) corresponds to the sample encompassing all observations within Luxembourg. Column (2) encompasses all observations outside Luxembourg. Column (3) refers to the observations located within 4 kilometres inside the Luxembourg border. Column (4) shows the observations located within 4 kilometres outside the Luxembourg border. As the number of observations can vary across implicates, we report the minimum and maximum number of observations.

Table 3: Means by border segment

	(1)	(2)	(3)	(4)
	Inside Luxembourg Full sample	Outside Luxembourg Full sample	4 km inside border	4 km outside border
Belgium				
Property price (thousands)	1140.0 (26.4)	448.2 (9.4)	953.5 (42.6)	430.7 (20.0)
Property size	187.5 (3.9)	207.5 (3.9)	176.4 (6.7)	190.2 (7.5)
Property age	35.7 (1.8)	46.8 (2.4)	41.8 (4.0)	43.7 (4.9)
Distance to city (Road)	(0.6) 22.9	(1.6) 66.7	(1.2) 34.0	(1.6) 48.1
House	(0.8) 80.2	(2.2) 95.2	(1.7) 81.4	(2.4) 92.2
Apartment	(1.8) 19.8	(1.0) 4.8	(3.4) 18.6	(2.8) 7.7
Minimum Observations	(1.8) 465	(1.0) 438	(3.4) 128	(2.8) 89
Maximum Observations	479	439	137	91
France				
Property price (thousands)	1067.9 (25.9)	373.7 (5.8)	945.2 (38.9)	415.6 (19.3)
Property size	150.6 (3.2)	151.2 (2.2)	153.4 (4.6)	142.3 (5.8)
Property age	40.8 (1.4)	44.7 (1.7)	44.1 (2.2)	38.4 (4.0)
Distance to city (Road)	12.6 (0.3)	47.0 (0.7)	20.7 (0.3)	25.5 (0.5)
House	61.7 (1.9)	85.7 (1.2)	71.0 (2.6)	84.8 (3.6)
Apartment	38.3 (1.9)	14.3 (1.2)	29.0 (2.6)	15.2 (3.6)
Minimum Observations	648	821	297	103
Maximum Observations	659	823	304	105
Germany				
Property price (thousands)	1069.8 (33.0)	506.0 (13.0)	927.1 (44.3)	608.9 (34.4)
Property size	189.6 (5.1)	172.1 (3.1)	187.6 (9.5)	178.0 (7.2)
Property age	37.2 (2.3)	31.7 (1.7)	32.8 (3.3)	23.6 (3.6)
Distance to city (Road)	(0.5) 28.1	(0.9) 55.1	(0.7) 32.6	(0.9) 38.8
House	(0.8) 81.8	(1.1) 87.1	(1.0) 76.7	(0.9) 93.5
Apartment	(2.2) 18.1	(1.8) 12.9	(4.1) 23.3	(3.2) 6.5
Minimum Observations	(2.2) 327	(1.8) 338	(4.1) 105	(3.2) 59
Maximum Observations	337	341	111	65

Notes: Standard errors are presented in parentheses. Column (1) corresponds to the sample encompassing all observations within Luxembourg. Column (2) encompasses all observations outside Luxembourg. Column (3) refers to the observations located within 4 kilometres inside the Luxembourg border. Column (4) shows the observations located within 4 kilometres outside the Luxembourg border. As the number of observations can vary across implicates, we report the minimum and maximum number of observations.

Beyond the price, the data reveal other structural differences: properties outside Luxembourg in the Belgian 4 km border segment tend to be larger (e.g., 190 m² in Belgium vs 176 m² inside) and slightly older. The opposite is true for the German and French 4 km border segments. Additionally, the share of apartments is higher in Luxembourg (both overall and at the border) than in neighbouring regions.

The descriptive statistics also anticipate the heterogeneity in the estimated border effects across country segments. Average prices within the 4 km strip on the Luxembourg side are comparable across the three border segments, ranging from approximately €927k near Germany to €954k near Belgium. By contrast, prices outside Luxembourg differ more substantially: the average value of properties within 4 km of the German border is about €609k, compared with roughly €431k on the Belgian side and €416k on the French side. This suggests that the smaller discontinuity estimated for the Luxembourg border with Germany is not primarily driven by unusually low prices on the Luxembourg side, but by higher prices in the German border area. The three border segments should therefore not be interpreted as equivalent replications of the same local experiment. They correspond to different local housing markets, with potentially different settlement density, accessibility to Luxembourg City and other employment centres, linguistic and cultural proximity, and residential preferences.

The detailed descriptive statistics highlight the presence of multiple confounding discontinuities, supporting our decision to use matching methods within a narrow geographical area rather than other quasi-experimental methods to estimate cross-border house price differences. Matching methods (e.g., propensity score or coarsened exact matching) allow us to pair observations inside and outside the border that are similar in terms of observed covariates, such as property size, age and distance to the city, and to compare outcomes such as prices more credibly. Matching on observed characteristics within a narrow border strip improves comparability between properties on opposite sides of the same border segment, while limiting the influence of geographical heterogeneity. This minimises bias from observable confounding factors, allowing us to focus on differences that can be plausibly attributed to a border effect. Although matching cannot entirely rule out unobservable factors, it is flexible in its ability to control for a broad set of covariates and impose a common support.¹⁵

¹⁵The lack of a clean assignment mechanism at the border and the presence of multiple confounding discontinuities render RD design unsuitable in this setting.

4 Results

This section presents the findings of our empirical analysis, employing hedonic regressions and kernel-based propensity-score matching. We use kernel-based PSM with regression adjustment as our preferred specification because, within the baseline 4 km strip, it offers a favourable balance for key continuous covariates, notably property size and distance to Luxembourg City. In the Appendix, we explore various restrictions to refine the selection of properties near Luxembourg’s border and evaluate alternative matching methods. Alternative matching methods yield similar estimates and are reported in the Appendix. Here, we report only the results of the selected matching method, which was chosen following diagnostic assessments detailed in the Appendix.

Table 4: Hedonic price model and propensity score matching results.

	(1)	(2) HPM	(3)	(4) PSM ⁺
	Full sample		4 km	
In Luxembourg	0.958*** (0.014)	0.822*** (0.017)	0.706*** (0.029)	0.737*** (0.029)
Size (m^2)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	
0-10 years	0.308*** (0.022)	0.292*** (0.021)	0.398*** (0.038)	
11-20 years	0.154*** (0.020)	0.144*** (0.020)	0.232*** (0.035)	
21-30 years	0.112*** (0.023)	0.107*** (0.022)	0.204*** (0.040)	
31-40 years	0.114*** (0.030)	0.107*** (0.029)	0.115* (0.056)	
41-50 years	0.095** (0.031)	0.086** (0.030)	0.172* (0.065)	
House	0.153*** (0.022)	0.164*** (0.021)	0.309*** (0.038)	
Germany	0.053** (0.019)	0.042* (0.019)	0.027 (0.035)	
France	0.036* (0.017)	-0.020 (0.017)	0.001 (0.035)	
Distance to city (Road)		-0.004*** (0.000)	-0.007*** (0.001)	
Constant	12.016*** (0.029)	12.253*** (0.033)	12.196*** (0.067)	
Observations				Matched:
Minimum	3055	3055	791	745
Maximum	3058	3058	807	777

Notes: ⁺Propensity score matching with regression adjustment for continuous variables. The dummies *Germany* and *France* indicate the property’s closest border, with *Belgium* as base category. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4 provides the results of the hedonic regression for the full and restricted samples, as well as the propensity

score matching analysis. The results of the different models are presented in different columns, enabling a direct comparison of the estimated coefficients and average treatment effects (ATE). Columns (1) to (3) present the results of the Hedonic Regression Model (HPM), where the dependent variable is the logarithm of the price and the border effect is represented by a dummy variable equal to one if the property is located within the Luxembourg border and zero otherwise. These same variables are used as matching attributes to implement the propensity score matching (PSM) procedure using a kernel matching procedure. This method uses all controls within a specified distance threshold, allocating greater weight to comparison of properties with more similar propensity scores. Column (4) displays the results using PSM kernel matching for the sample of properties located within 4 kilometres of either side of the border. Unlike the HPM results, the PSM specification matches the control and treatment observations exactly for the border segment of each country pairing, and includes post-matching regression adjustment with size and distance as the continuous adjustment variables.

First, we simply inspect the results using the full sample, without considering the distance to Luxembourg city centre (i.e. the central business district (CBD)). Without considering the geographical location of the property, we observe that a property in Luxembourg is, on average, valued 1.6 times more (i.e. $e^{0.958} - 1 = 161\%$) than if it were located in either Belgium, France or Germany. When we consider the geographical location by introducing the distance to the CBD, the difference reduces to 128% (i.e. $e^{0.822} - 1 = 128\%$). Next, we select a sample of properties within 4 kilometres on either side of the border. Considering this selective sub-sample, the house price discontinuity reduces to a ratio of 2.0, suggesting that houses are on average twice as expensive on the Luxembourg side of the border. Similarly, the propensity score matching analysis yields a *slightly higher* average treatment effect (ATE) than the hedonic regression for the restricted sample (109% versus 103%). This last estimation not only trims the sample to include only similar properties but also forces properties to be matched to the correct country pairing based on the border segment. Moreover, PSM can accommodate non-linear relationships between covariates and the outcome variable, unlike our linear specification.

When we break down the analysis by border segment and estimate the results for each of the three borders individually, we find that the estimated coefficients are closely comparable for both the HPM and PSM kernel methods with regression adjustment. Table 5 summarises these findings. For the 148 km (92 mi) Belgium–Luxembourg border, the estimation results suggest property prices are 112% higher in the PSM⁺ and 116% higher in the HPM specification on the Luxembourg side. A similarly sized border effect is estimated for the 73 km (45 mi) long France–Luxembourg border. Properties located within a distance of 4 km from the border are estimated to be 111% and 123% more expensive on the Luxembourg side, depending on the estimation method used. The price effect is smaller for the 138 km (86 mi) long Luxembourg–Germany border. For properties located within a 4 km strip on either side of the border, the estimated border effect is 35% in the PSM⁺ specification and 56% in the HPM specification. The PSM⁺ estimates are consistently lower than the corresponding HPM estimates, with the largest difference observed at the

Table 5: Hedonic price model and propensity score matching results at 4 kilometres along the border, by border segment.

	(1)	(2)	(3)	(4)	(5)	(6)
	Belgium		Germany		France	
	HPM	PSM ⁺	HPM	PSM ⁺	HPM	PSM ⁺
In Luxembourg	0.768*** (0.051)	0.753*** (0.059)	0.444*** (0.070)	0.302** (0.091)	0.800*** (0.042)	0.746*** (0.054)
Size (m^2)	0.003*** (0.000)		0.002*** (0.000)		0.004*** (0.000)	
0-10 years	0.326*** (0.065)		0.463*** (0.100)		0.371*** (0.054)	
11-20 years	0.166* (0.067)		0.307** (0.097)		0.249*** (0.047)	
21-30 years	0.155* (0.069)		0.218* (0.103)		0.217*** (0.059)	
31-40 years	0.123 (0.109)		0.128 (0.132)		0.123 (0.073)	
41-50 years	0.122 (0.112)		0.250 (0.166)		0.176* (0.086)	
House	0.278*** (0.078)		0.410*** (0.094)		0.252*** (0.049)	
Distance to city (Road)	-0.006*** (0.001)		-0.009* (0.003)		-0.007* (0.003)	
Constant	12.191*** (0.099)		12.503*** (0.185)		12.082*** (0.104)	
Observations	Matched:		Matched:		Matched:	
Minimum	219	206	165	161	402	395
Maximum	228	218	176	173	407	401

Notes: ⁺Propensity score matching with regression adjustment for continuous variables.

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

German border.

The lower estimate at the Luxembourg–Germany border deserves some comment. While the estimated coefficient remains positive and statistically significant (see Table 5), the result indicates a smaller price discontinuity than at the Belgian and French borders. This difference is already visible in the descriptive statistics. Average property values within the Luxembourg 4 km strip are comparable across the three border segments, while average values outside Luxembourg are substantially higher near the German border than near the Belgian or French border segments. The smaller Luxembourg–Germany discontinuity primarily reflects the higher underlying price level of housing on the German side of the border. Independent market data show that housing prices in the German part of the Greater Region are higher on average than in the corresponding Belgian and French parts.¹⁶ This may reflect differences in local economic conditions, settlement structure, housing supply, accessibility to regional centres, and national institutional environments. The estimated border-segment effects should therefore be interpreted as reduced-form differences between distinct local housing markets rather than as three otherwise identical border experiments. Since

¹⁶See Górczyńska-Angiulli et al. (2024).

these mechanisms are not all directly observed in the data, the border-segment estimates should be interpreted as reduced-form border effects that combine institutional differences with segment-specific geography, accessibility and sorting.¹⁷

Propensity score matching (PSM) is employed in this analysis due to the lack of continuity in observed property characteristics at the geographic boundary, which is a key assumption of the regression discontinuity design (RDD). To assess the sensitivity of our PSM estimates to unobserved confounding factors, we conducted a Rosenbaum bounds analysis (see [Rosenbaum, 2002](#), and [DiPrete and Gangl, 2004](#)). The results indicate that the treatment effect on $\log(\text{hmr price})$ remains significant ($p < 0.01$) even at $\Gamma = 5$, meaning that an unobserved confounder would need to increase the odds of a property being located in Luxembourg by more than fivefold to overturn our findings. With upper-bound p-values of zero across all tested Γ values, the estimates appear robust to sizeable hidden bias in the Rosenbaum-bounds framework. This supports the interpretation that the estimated discontinuities at the border are not solely driven by moderate unobserved selection on the location side of the border.

4.1 Varying the width of the strip from the border

We investigate how our results change when we vary the permitted distance from the border. Adjusting the distance of the strip not only changes the composition of the properties included in the comparison but also affects the extent to which location-specific factors, other than the border itself, influence house prices.

For example, narrowing the strip would restrict the comparison to properties "outside" the border with better public transport links to Luxembourg but would lower the sample size of matched properties. Conversely, widening the strip would most likely result in the inclusion of more distant properties, thereby increasing the sample size of matched properties. Inside the border, these properties may be located closer to Luxembourg's city centre whereas outside the border, they are likely to be owned by cross-border commuters with longer commutes or be closer to other central business districts, such as Trier (DE), Arlon (BE) and Thionville (FR). Therefore, selecting a wide strip can affect the estimated impact on house prices and bias the border effect estimates.

This issue is particularly relevant when comparing the three border segments. The Belgian, French and German borders differ not only in national laws and policies, but also in the density of nearby settlements, the presence of alternative urban centres, road and public-transport accessibility, and the degree to which cross-border residence is a close substitute for living in Luxembourg. For instance, higher prices on the German side of the border may partly reflect stronger local housing demand, proximity to Trier and other employment centres, or easier residential substitutability with Luxembourg. The segment-specific estimates should therefore be interpreted as reduced-form

¹⁷Estimation uncertainty alone is unlikely to account for the full difference: in the PSM⁺ specification, the German coefficient is 0.302 with a standard error of 0.091, while the Belgian and French coefficients are 0.753 and 0.746 with standard errors of 0.059 and 0.054, respectively. Nevertheless, the comparison across border segments should be interpreted with caution because each segment has a different matched sample and local market structure.

border effects that combine the effect of the national border with local geography, accessibility, settlement patterns and cross-border sorting.

Table 6 reports estimates using strips of 3, 4 and 5 kilometres on either side of the border. The estimated border effect is remarkably stable across these alternative distance thresholds. In the PSM⁺ specification, the estimated price premium is 111% for the 3-kilometre strip, 109% for the baseline 4-kilometre strip and 112% for the 5-kilometre strip. The HPM estimates display a similarly stable pattern, ranging from approximately 102% to 107%. Widening the strip increases the number of available observations and correspondingly improves precision, while narrowing it produces somewhat larger standard errors. Importantly, however, all estimated border effects remain highly statistically significant across the three distance thresholds. These results indicate that the estimated Luxembourg housing premium is not sensitive to the precise choice of the border strip within the 3–5 kilometre range. We retain the 4-kilometre strip as our baseline specification because it provides a compromise between restricting the comparison to geographically close dwellings and maintaining a sufficiently large sample for matching and estimation.

Table 6: Hedonic price model and propensity score matching results at the border

	3 km		4 km		5 km	
	HPM	PSM ⁺	HPM	PSM ⁺	HPM	PSM ⁺
In Luxembourg	0.703*** (0.032)	0.747*** (0.033)	0.706*** (0.029)	0.737*** (0.030)	0.727*** (0.024)	0.751*** (0.028)
Size (m^2)	0.003*** (0.000)		0.003*** (0.000)		0.003*** (0.000)	
0-10 years	0.398*** (0.041)		0.398*** (0.038)		0.375*** (0.030)	
11-20 years	0.225*** (0.040)		0.232*** (0.035)		0.214*** (0.031)	
21-30 years	0.208*** (0.046)		0.204*** (0.040)		0.197*** (0.032)	
31-40 years	0.117 (0.060)		0.115* (0.056)		0.114* (0.048)	
41-50 years	0.147 (0.074)		0.172* (0.065)		0.108* (0.052)	
House	0.310*** (0.044)		0.309*** (0.038)		0.281*** (0.032)	
Germany	0.036 (0.041)		0.027 (0.035)		0.008 (0.029)	
France	-0.009 (0.039)		0.001 (0.035)		-0.032 (0.028)	
Distance to city (Road)	-0.008*** (0.001)		-0.007*** (0.001)		-0.007*** (0.001)	
Constant	12.227*** (0.079)		12.196*** (0.067)		12.262*** (0.053)	
Observations	Matched:		Matched:		Matched:	
Minimum	648	606	791	745	1121	1049
Maximum	660	613	807	777	1132	1068

Notes: ⁺Propensity score matching with regression adjustment for continuous variables.

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: Hedonic price model and propensity score matching results at 4 kilometres along the border, by housing type.

	(1)	(2)	(3)	(4)
	Houses		Apartments	
	HPM	PSM ⁺	HPM	PSM ⁺
In Luxembourg	0.699*** (0.033)	0.721*** (0.037)	0.781*** (0.061)	0.810*** (0.053)
Size (m^2)	0.003*** (0.000)		0.008*** (0.001)	
0-10 years	0.416*** (0.043)		0.228** (0.080)	
11-20 years	0.250*** (0.042)		0.112 (0.069)	
21-30 years	0.240*** (0.046)		0.023 (0.077)	
31-40 years	0.143* (0.060)		-0.097 (0.114)	
41-50 years	0.171* (0.073)		0.132 (0.127)	
Germany	0.035 (0.040)		-0.068 (0.076)	
France	-0.011 (0.041)		0.045 (0.063)	
Distance to city (Road)	-0.007*** (0.001)		-0.004 (0.002)	
Constant	12.546*** (0.071)		11.791*** (0.141)	
Observations		Matched:		Matched:
Minimum	628	587	161	150
Maximum	641	598	166	154

Notes: ⁺Propensity score matching with regression adjustment for continuous variables.
Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.2 Houses versus apartments

Table 7 presents the estimated border effects separately for houses and apartments, using the Hedonic Price Model (HPM) and propensity score matching with regression adjustment (PSM⁺). The border effect is confirmed for both property types, with ATE values ranging from 101% (HPM) to 106% (PSM⁺) for houses, and from 118% (HPM) to 125% (PSM⁺) for apartments. The results highlight a slightly higher price discontinuity for apartments than for houses.

Other factors also affect property prices, particularly the age and size of the property. Size has a positive and significant effect on property prices, with an increase of one square metre associated with an increase in the property value of 0.8% for apartments and 0.3% for houses. The coefficient estimate for property age varies more noticeably for houses, with the largest coefficient estimates (51%) being found for newer properties (less than 10 years old). The results also suggest larger effects for the youngest apartments. However, no statistically significant effects were found

for other age categories, which is likely related to the small sample size. Distance from Luxembourg city centre is another relevant factor, with a small but significant negative effect on house prices. This means that, on average, the further a house is from the city centre, the lower its value. However, distance is not statistically significant for apartments at the border.

4.3 Potential sources of bias

Neither multivariate regression analysis nor matching methods can account for all potential unmeasured confounding factors. In particular, matching methods depend on the "ignorability" assumption, also known as "no unmeasured confounding", which presumes that there are no unobserved differences between the treatment and control groups, given the observed covariates. This is rarely the case with real data. As this assumption cannot be formally tested, we perform different sensitivity analyses to assess its validity.

Random treatment allocation: To test for systematic bias or unobserved factors, we randomly allocate properties to a postcode inside or outside of Luxembourg's border and recalculate the distance. This serves as a quality check, demonstrating that the empirical model genuinely captures the discontinuity and not noise or random variation. Table 8 summarises the results under random postcode assignment for both the Hedonic Price Model (HPM) and the Propensity Score Matching (PSM⁺). Results are provided for varying distances (i.e., 3 km, 4 km and 5 km). The placebo ATEs (Average Treatment Effects) across all models are small and statistically not significant, suggesting that the price discontinuity disappears under random postcode assignment to properties. The values show no meaningful impact on property prices based on random assignment within these distances. These results corroborate our findings and suggest that the significant effects observed elsewhere in the model are likely to be due to real treatment variables rather than random chance.

By contrast, variables related to property characteristics, such as size, consistently demonstrate a positive effect across all distance thresholds and models. Property age also has a positive effect, particularly for newer constructions: properties in the first age category show strong, positive, significant effects. For older properties, the effects are generally weaker, though still significant in some cases. Road distance to the Luxembourg city centre has a consistently negative and significant impact on prices, with properties further from the city centre seeing lower prices, particularly at the 5 km distance. The consistency of these results across both models highlights their robustness in explaining property price variations.

Spurious border: A spurious border test involves using artificially created or irrelevant borders as a placebo to examine whether a model incorrectly attributes significant effects to these "fake" borders, which should have no impact on the outcome. In the context of house price studies, a spurious border would be a boundary with no real significance, such as an irrelevant geographical line. The idea behind this test is to determine whether the model

Figure 5: Placebo - Random assignment representation

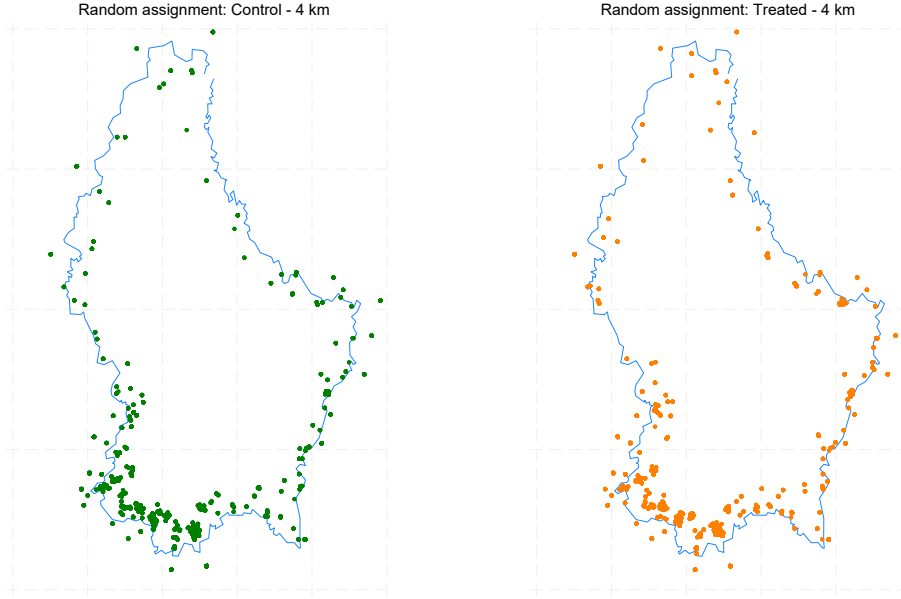


Table 8: Hedonic price model and propensity score matching results - Random treatment assignment

	3 km		4 km		5 km	
	HPM	PSM	HPM	PSM	HPM	PSM
Placebo border effect	-0.0350 (-0.46)	-0.0338 (-0.56)	-0.0391 (-0.59)	-0.0521 (-0.86)	-0.0285 (-0.58)	-0.0412 (-0.84)
Size (m^2)	0.00399*** (6.96)		0.00384*** (7.96)		0.00361*** (7.86)	
0-10 years	0.290*** (4.71)		0.303*** (5.33)		0.288*** (4.85)	
11-20 years	0.0839 (0.93)		0.111 (1.44)		0.123 (1.57)	
21-30 years	0.251** (2.66)		0.245** (2.73)		0.236** (3.24)	
31-40 years	0.111 (1.27)		0.139 (1.54)		0.181* (2.36)	
41-50 years	0.279** (3.16)		0.287*** (3.79)		0.170* (2.30)	
House	0.0659 (0.93)		0.102 (1.58)		0.0409 (0.79)	
Distance to city (Road)	-0.0105*** (-5.84)		-0.0135*** (-11.98)		-0.0154*** (-9.56)	
Constant	12.90*** (169.65)		12.97*** (176.36)		13.02*** (176.41)	
<i>Observations</i>						
Minimum	648	618	791	747	1121	1058
Maximum	660	627	807	765	1132	1080

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

correctly captures the true border effects; any fake allocation or border should yield insignificant results.

To evaluate the robustness of the estimated border effect, we rescale the Luxembourg border by making it larger or smaller while maintaining its original shape. Specifically, we increase or decrease the distance of each border point from a reference centre, defined as the mean latitude and longitude of the original border points, by a given percentage (θ). For example, increasing the border size by 50% means multiplying each point's deviation from the reference centre by 1.5. This transformation preserves the border's overall shape while creating an artificial boundary further inside or outside its original location. For each rescaled border, we recalculate the distance of each property to the artificial boundary and determine whether it lies inside or outside it. We then repeat the estimation to examine whether comparable price differences are also detected at these artificial boundaries. Since these boundaries do not correspond to the actual national border, the exercise provides a placebo test of whether the estimated price discontinuity is specific to the real border.

Table 9: Hedonic price model and propensity score matching results at artificially expanded and contracted borders.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	HPM	PSM ⁺	HPM	PSM ⁺	HPM	PSM ⁺	HPM	PSM ⁺	HPM	PSM ⁺	HPM	PSM ⁺
	+45%	+45%	+50%	+50%	+55%	+55%	-55%	-55%	-50%	-50%	-45%	-45%
In Luxembourg	0.116** (0.042)	0.005 (0.056)	0.011 (0.042)	0.017 (0.069)	-0.008 (0.030)	0.032 (0.033)	0.040 (0.030)	0.021 (0.031)	-0.019 (0.032)	0.046 (0.040)	-0.036 (0.039)	-0.046 (0.037)
Size (m^2)	0.003*** (0.000)		0.004*** (0.000)		0.003*** (0.000)		0.003*** (0.000)		0.003*** (0.000)		0.003*** (0.000)	
Less 10 years	0.346*** (0.046)		0.319*** (0.047)		0.139** (0.044)		0.130** (0.045)		0.141** (0.045)		0.121* (0.049)	
11-20 years	0.194*** (0.047)		0.199*** (0.048)		0.034 (0.046)		0.014 (0.044)		0.010 (0.047)		0.014 (0.051)	
21-30 years	0.192** (0.060)		0.186** (0.060)		0.056 (0.052)		0.058 (0.053)		0.058 (0.050)		0.051 (0.052)	
31-40 years	0.118 (0.091)		0.157 (0.086)		0.124* (0.059)		0.074 (0.054)		0.067 (0.052)		0.049 (0.055)	
41-50 years	-0.100 (0.101)		-0.079 (0.094)		0.103 (0.055)		0.063 (0.055)		0.061 (0.056)		0.057 (0.060)	
House	0.174** (0.056)		0.143* (0.058)		0.140*** (0.041)		0.105* (0.044)		0.088 (0.045)		0.064 (0.048)	
Distance to city	-0.004*** (0.001)		-0.004*** (0.001)		-0.012*** (0.001)		-0.012*** (0.001)		-0.012*** (0.001)		-0.012*** (0.001)	
Constant	12.125*** (0.080)		12.171*** (0.086)		13.332*** (0.045)		13.358*** (0.043)		13.362*** (0.043)		13.375*** (0.050)	
Observations												
Minimum	611	585	618	592	672	611	655	622	642	626	554	384
Maximum	622	602	629	613	680	625	667	634	654	642	565	392

Notes: ⁺Propensity score matching with regression adjustment for continuous variables.Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9 presents the results from the Hedonic Price Model (HPM) and Propensity Score Matching (PSM⁺) after the border coordinates were rescaled by different percentages, either increasing or decreasing the border size by 45%, 50%, and 55%. In general, the results show that rescaling the border renders most coefficient estimates statistically not significant.

For instance, with a 45% increase in border size, the border effect remains significant in the HPM model, suggesting that there may be unobserved determinants that the HPM model captures. However, it is insignificant in the PSM⁺, possibly because confounding unobserved variables are better isolated. As the border is moved further by increasing it by 50% and 55%, the border effect loses significance entirely in both models, with near-zero, statistically insignificant coefficients. Similarly, when the border is decreased by 45%, 50%, and 55%, the estimated difference is always insignificant in both models. These results suggest that the effect disappears if the border is artificially rescaled, which supports the validity of the original border effect detected in earlier models.

Other key factors such as the size and age of the property remain significant across the models and rescaling tests. Property size continues to have a positive and statistically significant effect on property prices, with coefficient estimates of around 0.003 in all scenarios. Similarly, newer properties (less than 10 years old) have a strong effect on property prices, while older properties show varying degrees of impact. Distance to the city consistently has a negative and significant effect on property prices. Overall, the results suggest that this rescaled or "fake" border has no influence on property prices, while other fundamental factors such as size, age, and proximity to the city remain robust across different model specifications.

5 Conclusions

National borders can create sharp discontinuities in housing markets. This paper analyses such house price discontinuities along the Luxembourg border with its three neighbouring countries Belgium, France and Germany. We compare properties with similar characteristics that are located within a narrow strip on either side of the border.

To achieve this, we employ hedonic price models and propensity score matching techniques with regression adjustment. These account for location and property characteristics, such as the respective national border, the property type, size and age. Our primary estimates are based on propensity score methods that explicitly consider differences in property characteristics within a 4 kilometre strip on either side of the border. We find significant heterogeneity in house price discontinuities across the three border segments (Belgium, France and Germany). The results are robust to varying the size of the strip and employing different methodologies.

Our results reveal a large price discontinuity at the borders of Luxembourg with Belgium and France, and a smaller yet still significant discontinuity at the border to Germany. After adjusting for property characteristics and location determinants, our preferred estimates suggest discontinuities of 112% and 111% for the borders with Belgium

and France, and a much lower discontinuity of 35% for the border with Germany.

The heterogeneity across border segments is itself informative. The smaller estimated discontinuity at the German border appears to reflect higher housing values on the German side, rather than lower prices on the Luxembourg side. This suggests that the segment-specific estimates capture not only national institutional differences, but also local market conditions, housing structure, accessibility and cross-border residential patterns. Since the available data do not allow us to separately identify these channels, the estimates should be interpreted as reduced-form border premiums.

From a methodological standpoint, our approach shows how combining geographical matching with propensity score techniques can be useful for estimating quality-adjusted near-border property price differences. The persistence of a discontinuity after controlling for these factors highlights the limitations of observable characteristics alone in explaining observed price differences. Although Luxembourg is a striking case study of how institutional, economic and social factors combine to create persistent housing market differences, our findings are relevant not only to Luxembourg, but also to other areas and regions spanning different jurisdictions.

Future research could build on this analysis by investigating whether the discontinuity has widened or narrowed over time and whether improved cross-border transport infrastructure and labour mobility act as equalising factors. Our results emphasise that substantial housing-price differences persist across national borders even in highly integrated cross-border regions such as the Greater Region.

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A Appendix

A.1 Matching methods and diagnostics

Multivariate Distance Matching (MDM) operates by matching units in proximity using a distance measure. The principle is to locate control units near treated ones based on this distance, ensuring similarity in the covariate distributions among matched pairs, meaning those in the treatment and control groups within the matched sample. MDM uses the following distance metric:

$$MD(X_i, X_j) = \sqrt{(X_i - X_j)' \Sigma^{-1} (X_i - X_j)}.$$

Where Σ is a scaling matrix that depends on the matching method. Euclidean matching would use Σ equal to the identity matrix. Another option is *Mahalanobis* matching, in which Σ is the covariance matrix of X . A Mahalanobis distance of 0 indicates identical covariate values between two units, while greater differences in the values of the covariates result in larger distances.

Propensity Score Matching (PSM) matches units based on the probability of assignment to treatment given a vector of covariates, known as the propensity score. In other words, propensity scores condense the entirety of the covariate distribution into a single dimension, implying that units with similar propensity scores may not have identical covariate values. Nonetheless, due to the theoretical balancing properties of propensity scores, PSM can generate balanced samples, despite that the matched pairs can potentially differ in terms of the covariate values. Any standard probability model can be used to estimate the propensity score, e.g. a logit or probit model. The distance metric using PSM is calculated as follows:

$$D(X_i, X_j) = |\pi(x_i) - \pi(x_j)|.$$

where $\pi(x_i)$ and $\pi(x_j)$ correspond to the propensity score for dwelling i and j respectively.

The key distinction between MDM and PSM is highlighted in the PSM critique of [King and Nielsen \(2019\)](#). While MDM aims to create pairs with similar covariate values, PSM does not prioritize this. Despite both methods potentially achieving balanced samples, [King and Nielsen \(2019\)](#) argue that PSM (one-to-one matching without replacement - pair matching) produces fragile and non-robust estimates, sensitive to the chosen outcome model.¹⁸ They discuss the propensity score paradox, where even though units close in propensity scores are retained, imposing stricter calipers can deteriorate balance. Consequently, they caution against PSM in favor of methods like MDM,

¹⁸Their argument boils down to the common issues of a *complete randomization* design (approximated by PSM), which can produce, just by chance, unbalanced groups regarding the observations' initial characteristics. In this respect, a *fully blocked* design (approximated by MDM), which reduces variability between groups, offers a gain in statistical power and precision, leading to less data imbalance and model dependency.

which directly match on covariate space for potentially more robust results.

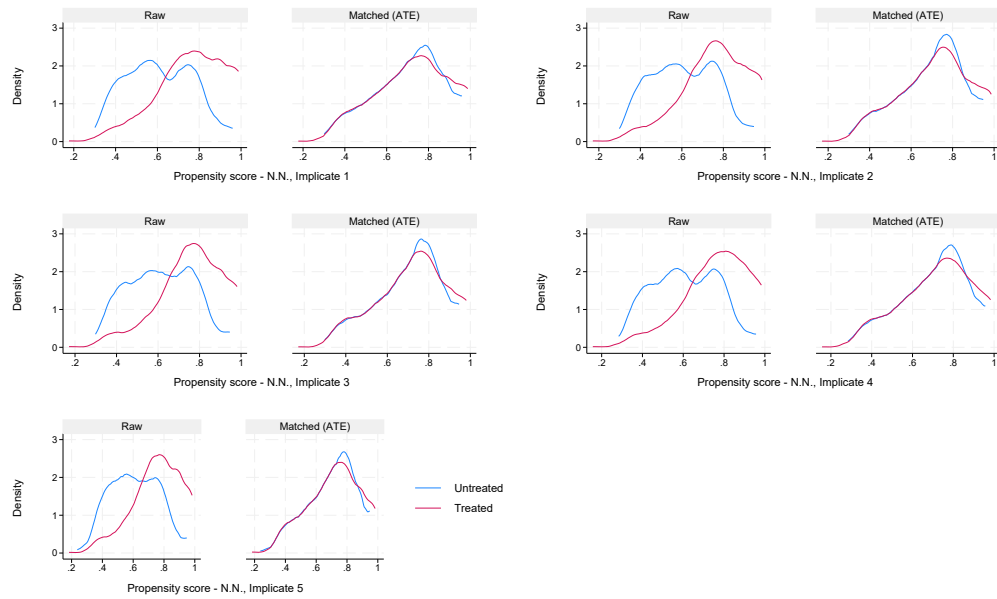
In contrast, [Ripollone et al. \(2018\)](#) examined the propensity score paradox using real epidemiological data. Their findings indicate that while the paradox can manifest in certain cases, it becomes problematic only with extreme caliper values, well beyond recommended thresholds. Generally, PSM maintains good covariate balance. Conversely, MDM exhibits poor balance for some datasets, occasionally worse than not matching at all. Particularly, MDM under-performs when the covariates matrix is high-dimensional and when the covariates are normally distributed or there are too many covariates ([Stuart, 2010](#)). Consequently, an increase in covariates leads to more complex interactions that need to be balanced. While the problem of high-dimensionality is reduced to a single dimensional problem using PSM, a problem arises when a large number of covariates are included in constructing the propensity score model, as it becomes more likely that individuals with similar propensity scores will have more divergent covariate profiles ([Ripollone et al., 2018](#)). In our scenario, we use 9 attributes for the matching, most of them come from the dichotomous variables created to represent different ranges of the age of the dwelling.

A.1.1 Diagnostics - Propensity Score Matching (PSM)

There are several methods to perform propensity score matching, including one-to-one, nearest neighbour matching (NN) with or without replacement, caliper and radius matching, kernel and local linear matching, weighting optimal matching, full matching, genetic matching, and PSM with coarsened exact matching ([Caliendo and Kopeinig, 2008](#); [King and Nielsen, 2019](#)). We performed estimations using both the NN with one-to-one matching with replacement and Kernel matching (Epanechnikov kernel function). For both algorithms, we enforce exact matching on the same "border segment".

We first check the assumption of common support, which ensures that dwellings with the same propensity score values have a positive probability of being in both Luxembourg (treatment) and neighbouring regions (non-treatment). Figures 6 to 11 present the density distributions of the propensity scores for the treated and untreated groups and for both the matched and raw sample.

Figure 6: Density of the propensity score before and after matching properties less than **3 km** away from the border using **nearest-neighbour matching**



Note: N.N refers to nearest-neighbour matching with 1 neighbour

Figure 7: Density of the propensity score before and after matching properties less than **3 km** away from the border using **kernel matching**

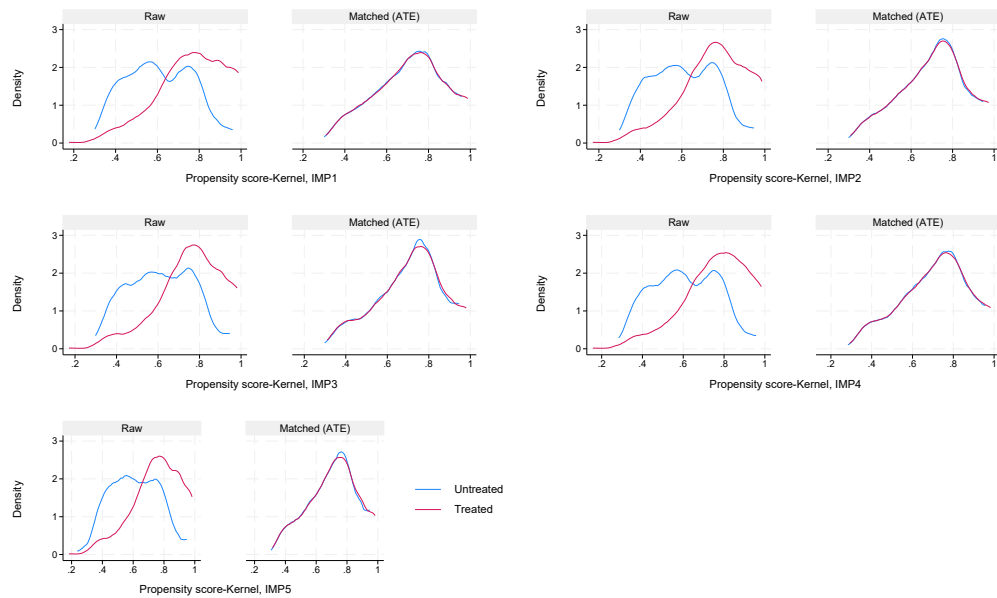
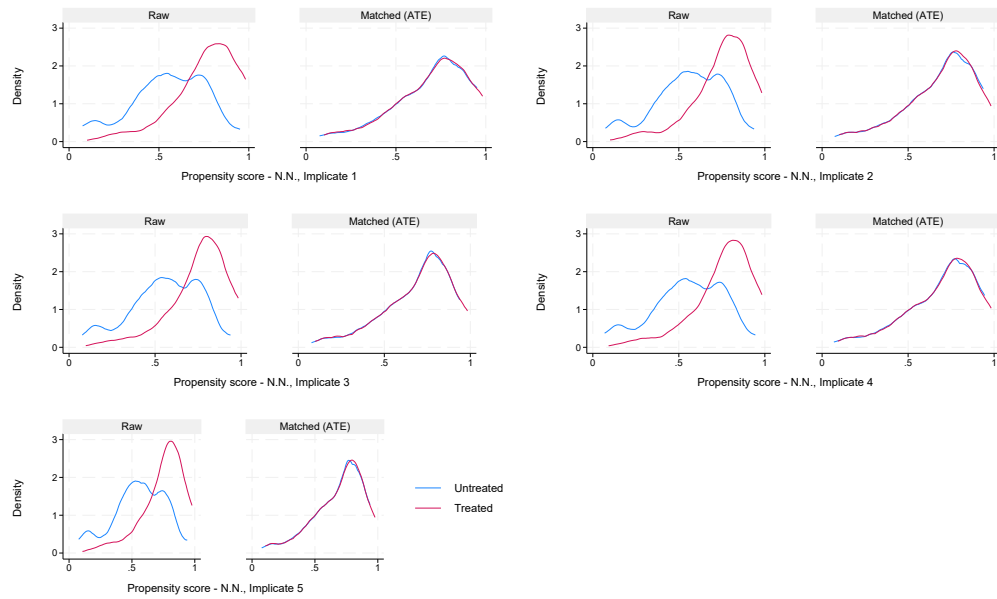


Figure 8: Density of the propensity score before and after matching properties less than **4 km** away from the border using **nearest-neighbour matching**



Note: N.N refers to nearest-neighbour matching with 1 neighbour

Figure 9: Density of the propensity score before and after matching properties less than **4 km** away from the border using **kernel matching**

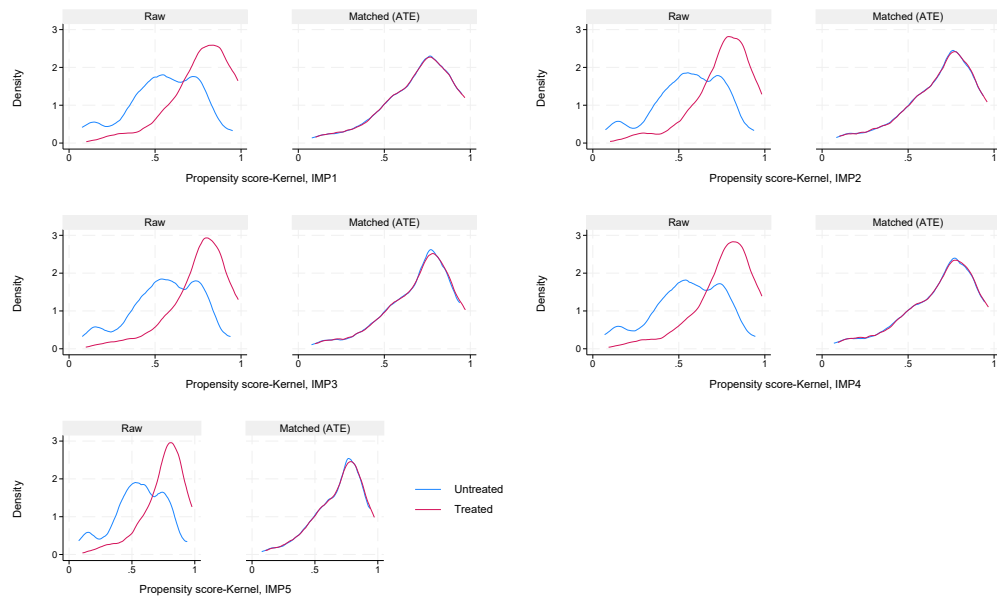
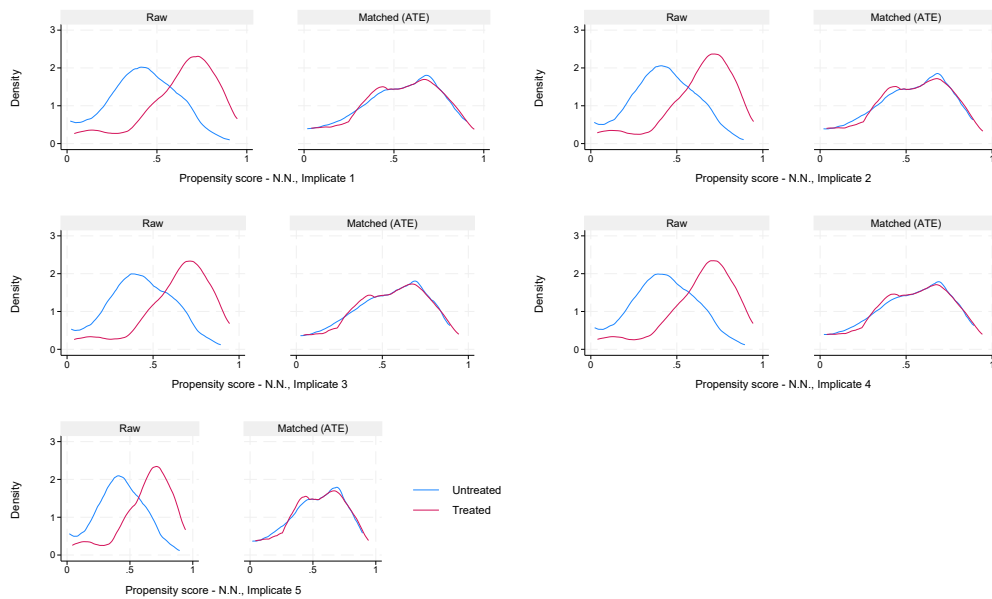
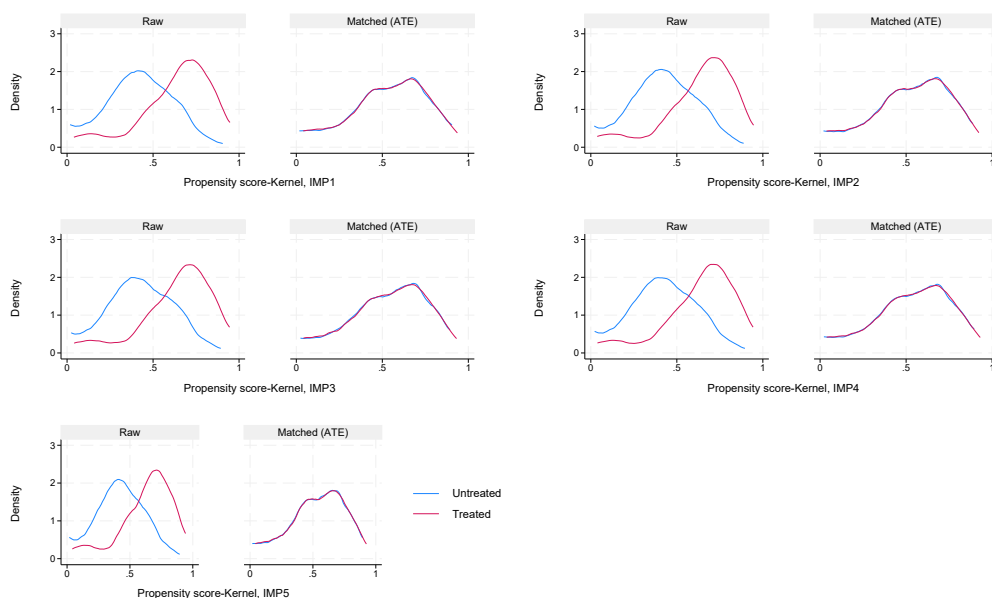


Figure 10: Density of the propensity score before and after matching properties less than **5 km** away from the border using **nearest-neighbour matching**



Note: N.N refers to nearest-neighbour matching with 1 neighbour

Figure 11: Density of the propensity score before and after matching properties less than **5 km** away from the border using **kernel matching**



We see that the matched sample (on the right panel) has overlapping lines, indicating that there are no large deviations. After matching is applied, the density of the propensity score of both groups are similar on average. At 3

kilometres from the border, we notice that the treated sample’s propensity distribution better matches the untreated group when employing kernel matching compared to nearest-neighbour matching with 1 neighbour, particularly evident for implicates 1, 2, and 4. At 4 kilometres from the border, we observe that the treated sample’s propensity distribution aligns better with the untreated group when using nearest-neighbour matching compared to the situated at 3 kilometres from the border in all implicates of the dataset. However, greater alignment is achieved with kernel matching. For the sample situated 5 kilometres away, the propensity distributions of the treated and untreated groups do not align well using nearest-neighbour matching compared to samples closer to the border. However, alignment improves significantly after employing kernel matching.

Overall, the choice of matching method—whether nearest-neighbour or kernel matching—significantly impacts the alignment of propensity distributions between treated and untreated groups across varying distances from the border. At 3 kilometres, kernel matching demonstrates superior alignment, particularly for specific implicates. At 4 kilometres, both methods show alignment, with kernel matching offering slightly better results. However, at 5 kilometres, nearest-neighbour matching struggles to achieve alignment, whereas kernel matching successfully aligns propensity distributions. These findings underscore the importance of selecting an appropriate matching method tailored to the size of the samples to ensure accurate analysis and interpretation of treatment effects.

Another way to evaluate the performance of a matching algorithm to balance the covariate is by quantifying the absolute standardized difference for each covariate in the attributes set. The standardized mean difference is calculated as the difference in sample means (or proportions for dichotomous variables) divided by the pooled standard deviation. Figure 12 confirms that after matching, the standardized mean differences of treatment and control groups are closer to zero, indicating that they are very similar to each other. Note that the variable indicating the closest border is not included in the figures since by design, the mean will be exact across groups.

The variance ratio was also calculated and presented in figures 12, 14, and 16. The ratio approaches one for most variables within the matched sample, in comparison to the raw sample, where there is a larger disparity between treatment and control group.

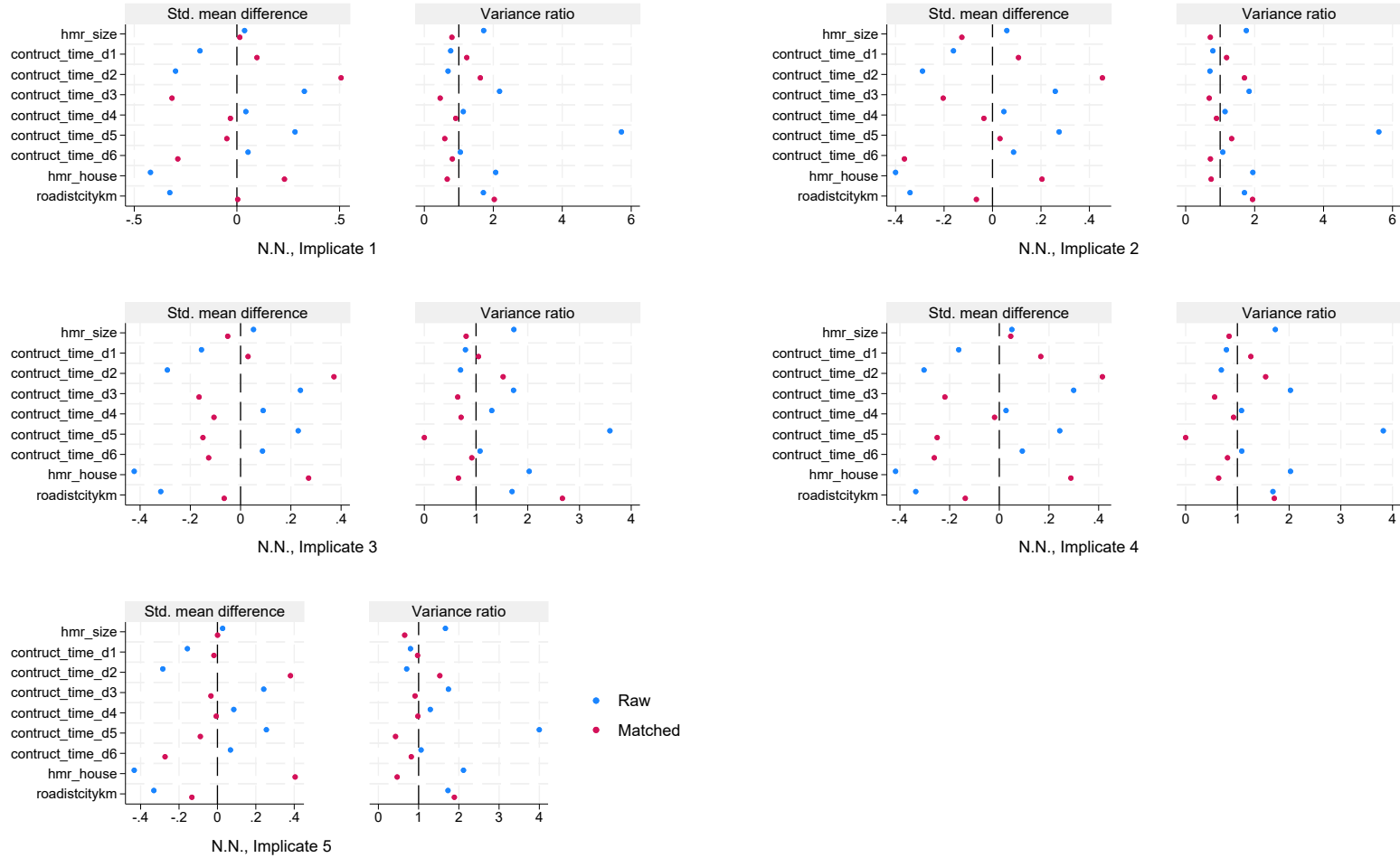
For the sample located 3 km from the border, when considering nearest-neighbour matching, the variable road distance has a superior similarity in standardized mean difference compared to kernel matching, while for other variables, kernel matching tends to match the treatment and control group means better across most implicates of the dataset. Kernel matching exhibits a better performance in terms of the variance ratio compared to nearest-neighbour matching since the ratios are closer to one.

In the case of the sample situated 4 km from the border, kernel matching generally provides better alignment for most variables across the dataset, except for road distance, for which both methods display poor alignment. Nonetheless, nearest-neighbour matching outperforms kernel matching in standardized mean difference for road distance. As expected, Kernel matching maintains an advantage in the variance ratio over nearest-neighbour matching.

For the sample positioned 5 km from the border, kernel matching emerges as the preferred method for matching most variables across the dataset, with superior performance in standardized mean difference and variance ratio, except for road distance, where nearest-neighbour matching yields better alignment in standardized mean difference.

In summary, the choice between nearest-neighbour matching and kernel matching for matching depends on the samples located at varying distances from the border, particularly as proximity to the border corresponds to smaller sample sizes. The selection of the matching algorithm becomes crucial in smaller samples, where there is a noticeable trade-off between variance and bias, as highlighted by [Caliendo and Kopeinig \(2008\)](#). While kernel matching generally demonstrates superior alignment for most variables across the dataset, nearest-neighbour matching performs better for road distance, particularly for samples closer to the border. Additionally, kernel matching consistently outperforms nearest-neighbour matching in terms of the variance ratio.

Figure 12: Diagnostics for properties less than **3 km** away from the border - **nearest-neighbour matching**



Note: N.N refers to nearest-neighbour matching with 1 neighbour

Figure 13: Diagnostics for properties less than 3 km away from the border - **kernel matching**

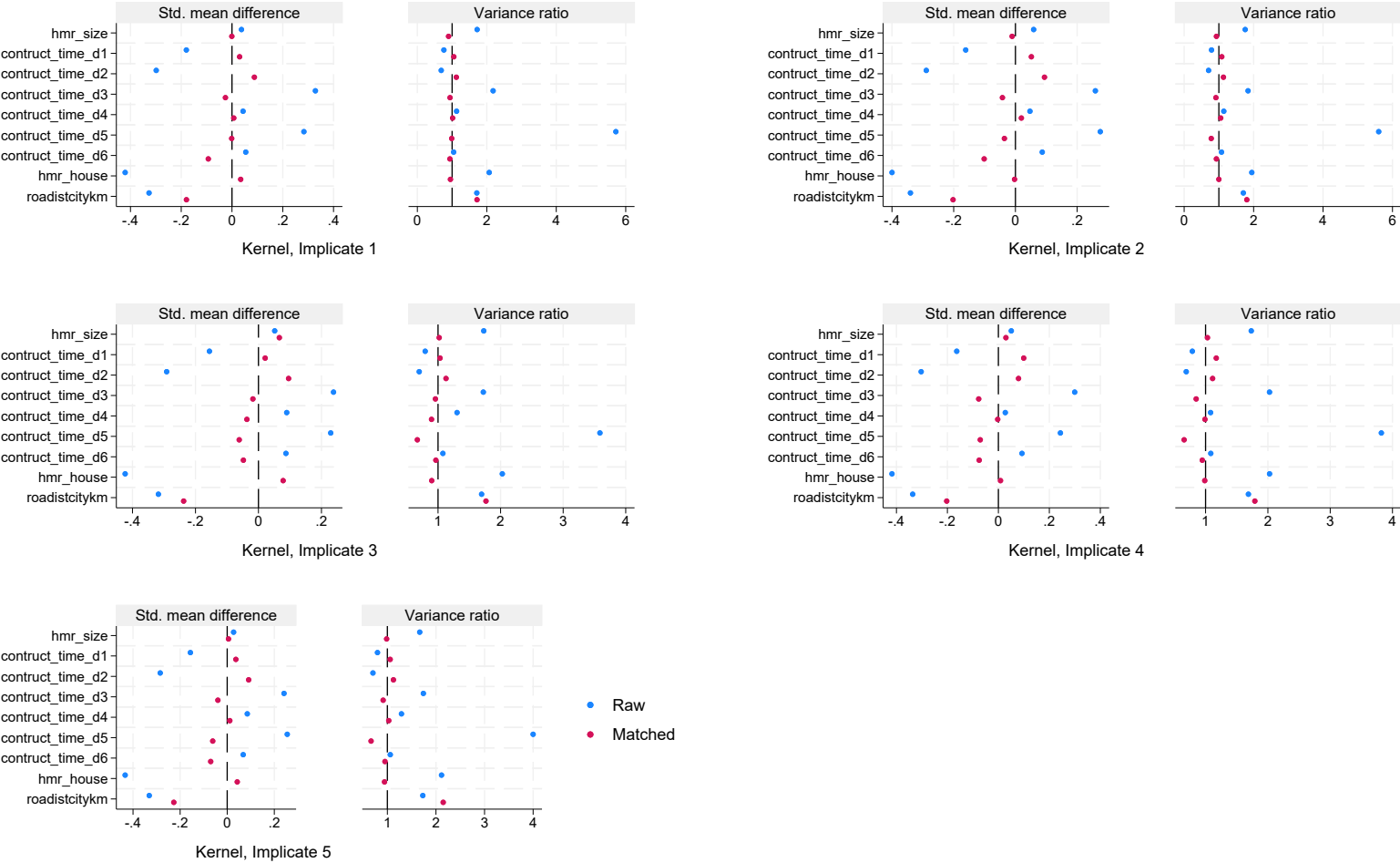
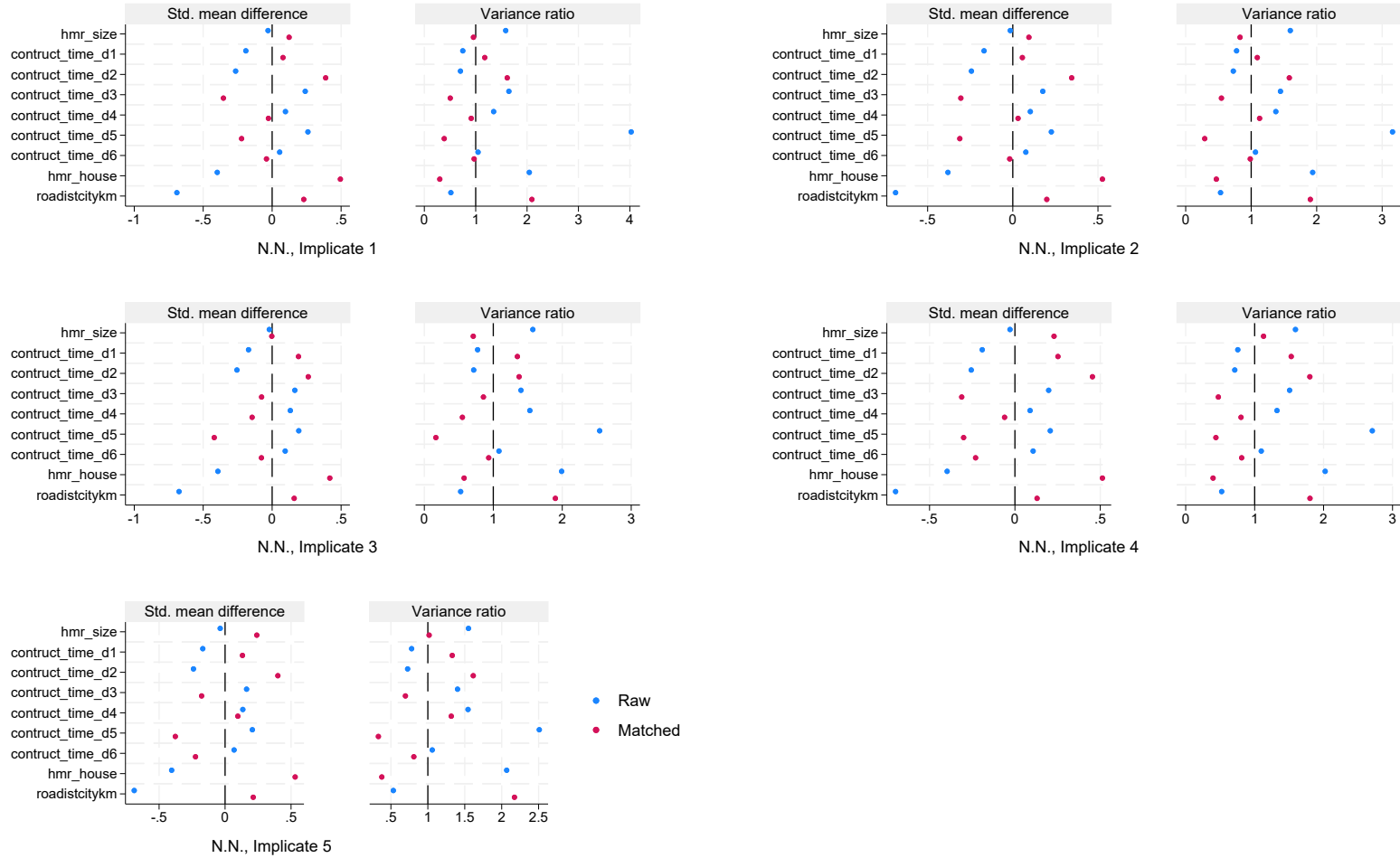


Figure 14: Diagnostics for properties less than 4 km away from the border - **nearest-neighbour matching**



Note: N.N refers to nearest-neighbour matching with 1 neighbour

Figure 15: Diagnostics for properties less than 4 km away from the border - **kernel matching**

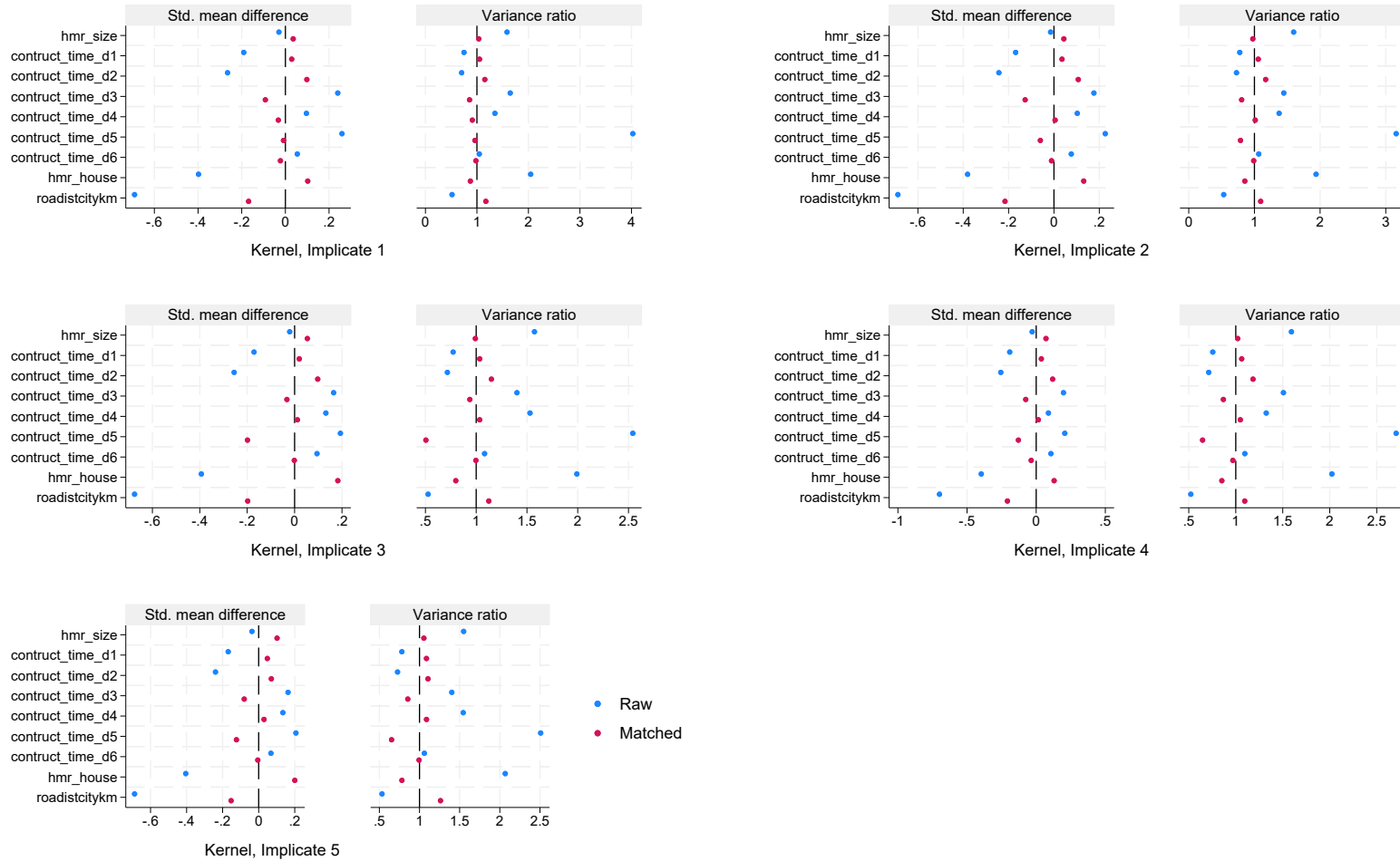
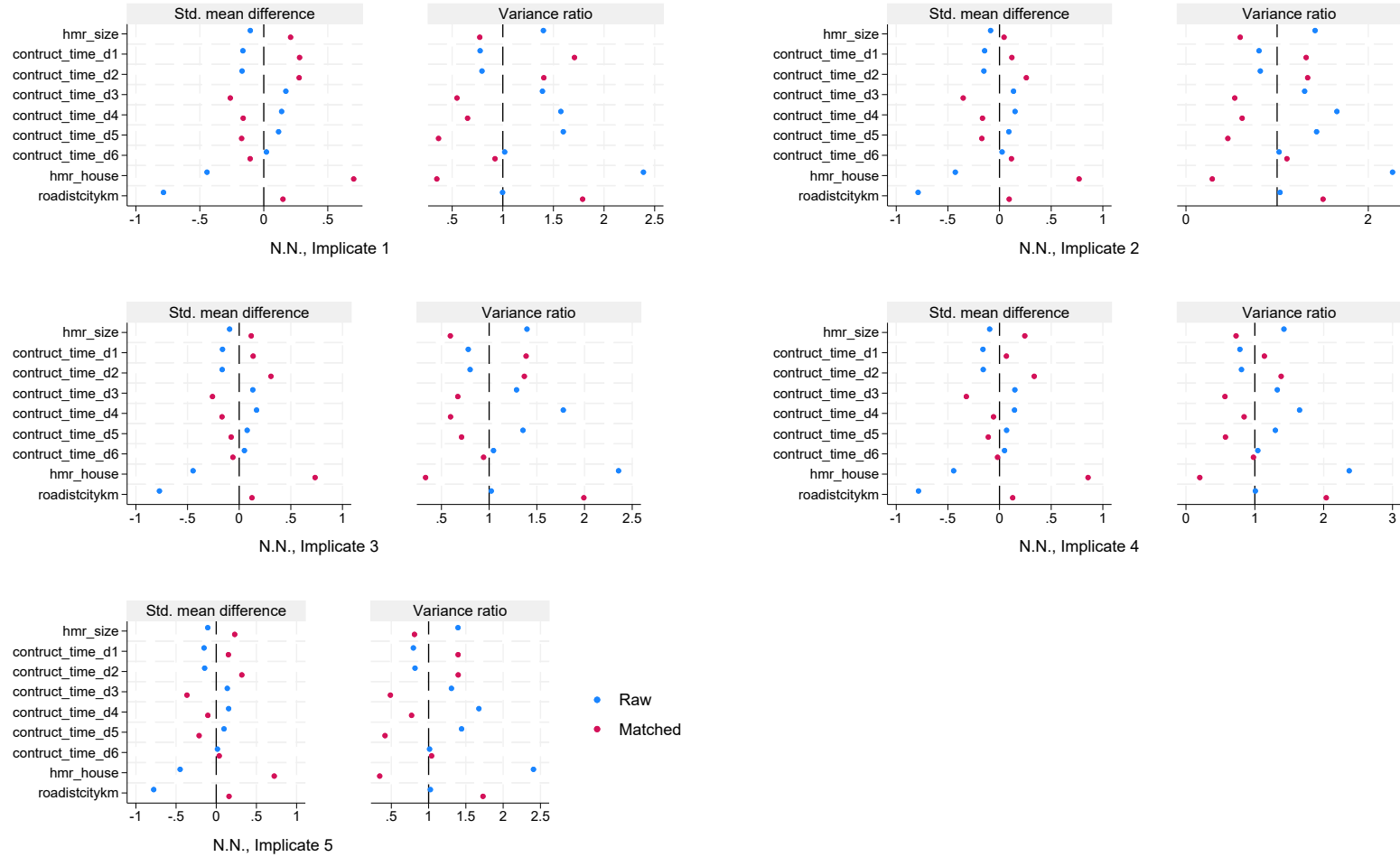
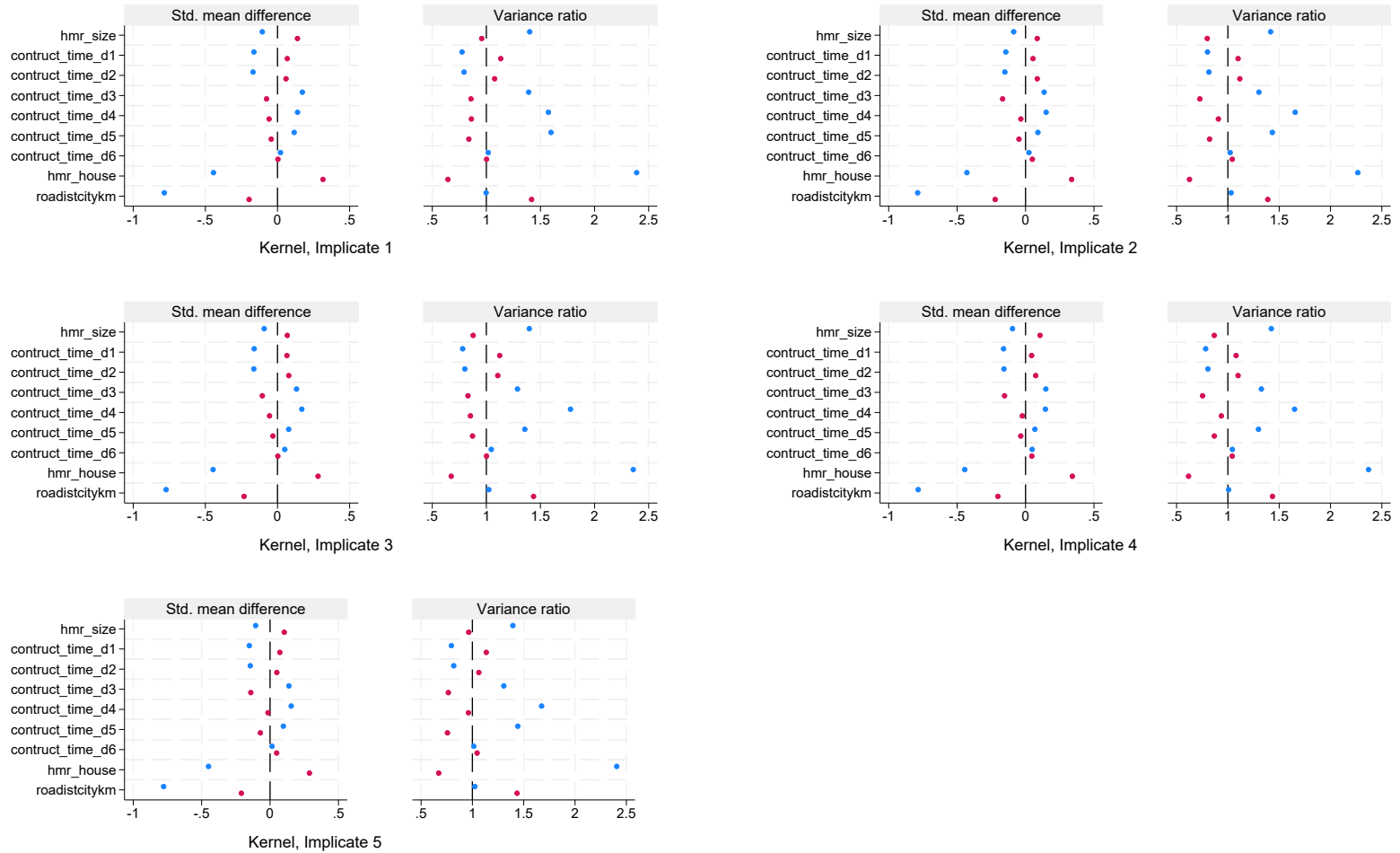


Figure 16: Diagnostics for properties less than 5 km away from the border - **nearest-neighbour matching**



Note: N.N refers to nearest-neighbour matching with 1 neighbour

Figure 17: Diagnostics for properties less than 5 km away from the border - **kernel matching**



A.1.2 Diagnostics - Multivariate Distance Matching (MDM)

Since our models consist of few covariates, we also provide estimates using a MDM with kernel matching algorithm, meaning that it gives more weight to observations with smaller distance (MD) using a kernel function. Since this method does not calculate propensity scores, we present the standardized mean difference and variance ratio as diagnostic measures in figures 18, 19, and 20. The figures show that at a distance of 3 kilometres from the border, Kernel matching demonstrates superior balance for variables like HMR size, type of property (house versus apartment), and road distance to the CBD compared to MDM, as indicated by the smaller standardized differences. However, the performance between the two methods is unclear for the variable *construction time*. Yet, MDM shows variance ratios closer to one compared to kernel matching. Within 4 kilometres from the border, kernel matching results in better balance for road distance and HMR size, with standardized mean differences closer to 0 compared to MDM. Conversely, MDM balances construction time and property type more effectively. Overall, MDM exhibits variance ratios closer to one across most variables. Moving to 5 km from the border, MDM generally achieves smaller standardized mean differences compared to kernel matching for most variables, except for road distance to the CBD, where kernel matching performs better. Additionally, MDM consistently yields variance ratios closer to one for all covariates compared to kernel matching.

Considering these findings, the choice between kernel matching and MDM depends on specific priorities. If prioritizing balance for variables like road distance and HMR size, particularly closer to the border, kernel matching may be preferred. However, for more comprehensive balance across various covariates and distances, MDM appears to offer more consistent results, especially in terms of minimizing standardized mean differences and maintaining variance ratios close to one.

Figure 18: Diagnostics for properties less than **3 km** away from the border - MDM

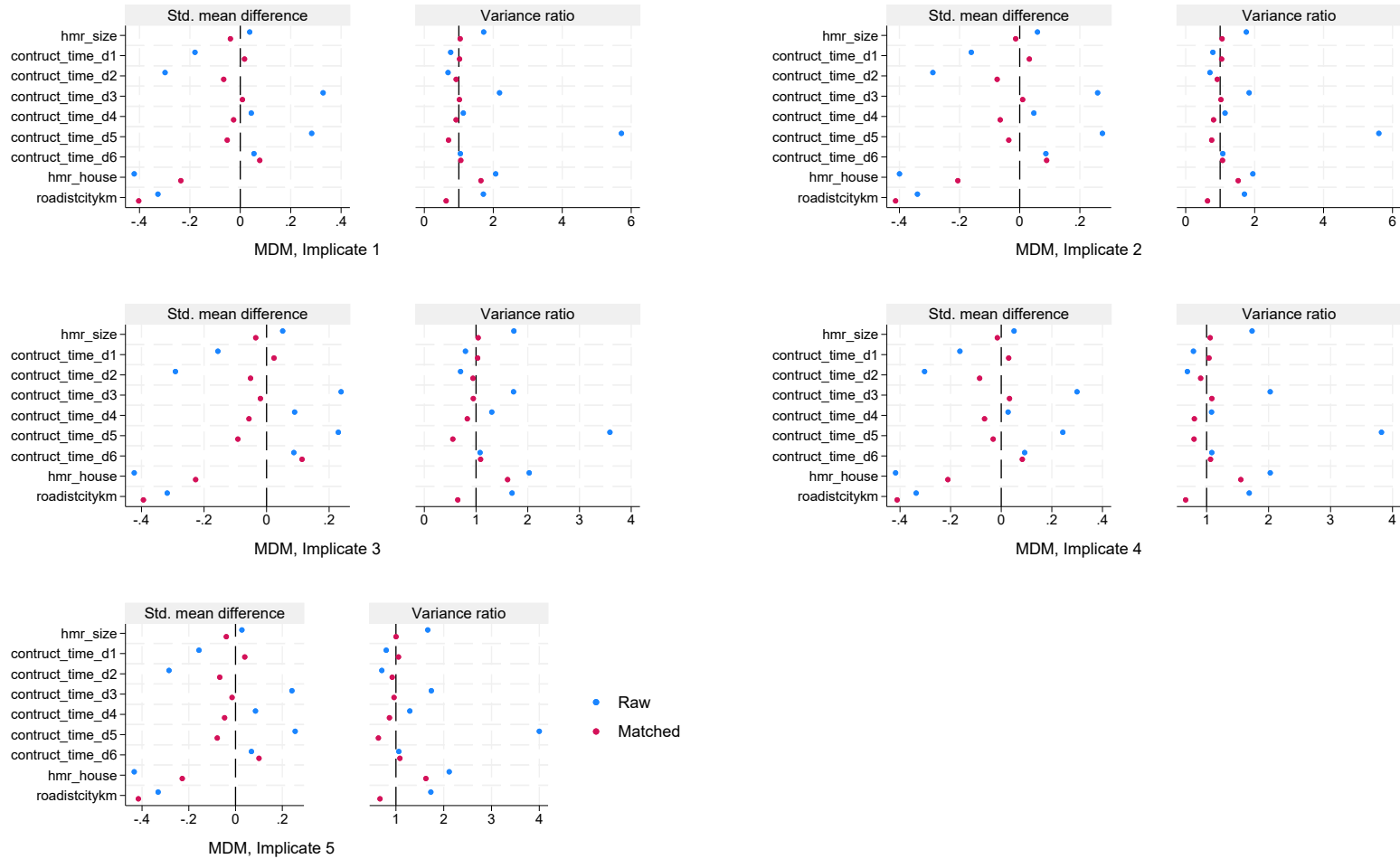


Figure 19: Diagnostics for properties less than 4 km away from the border - MDM

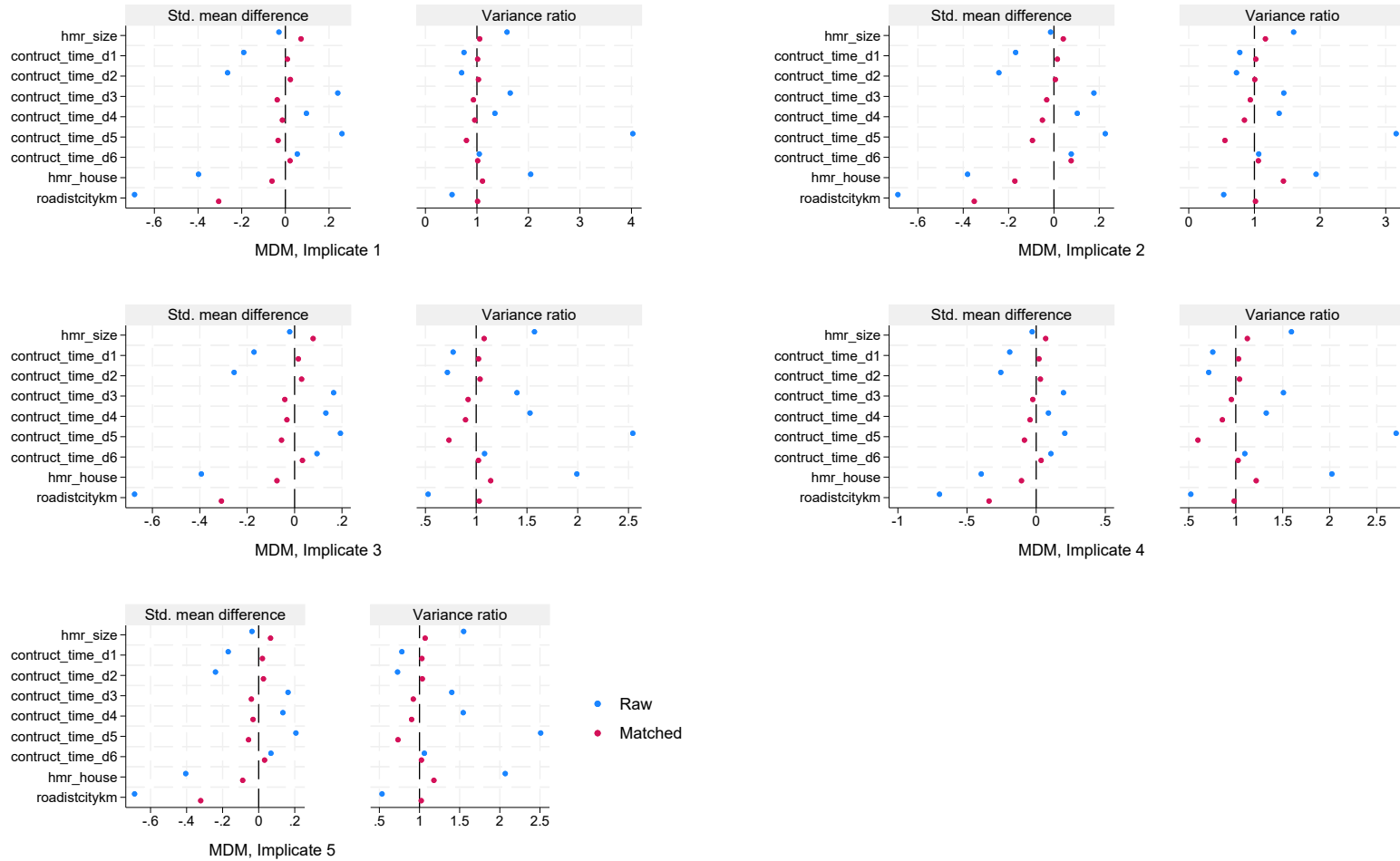
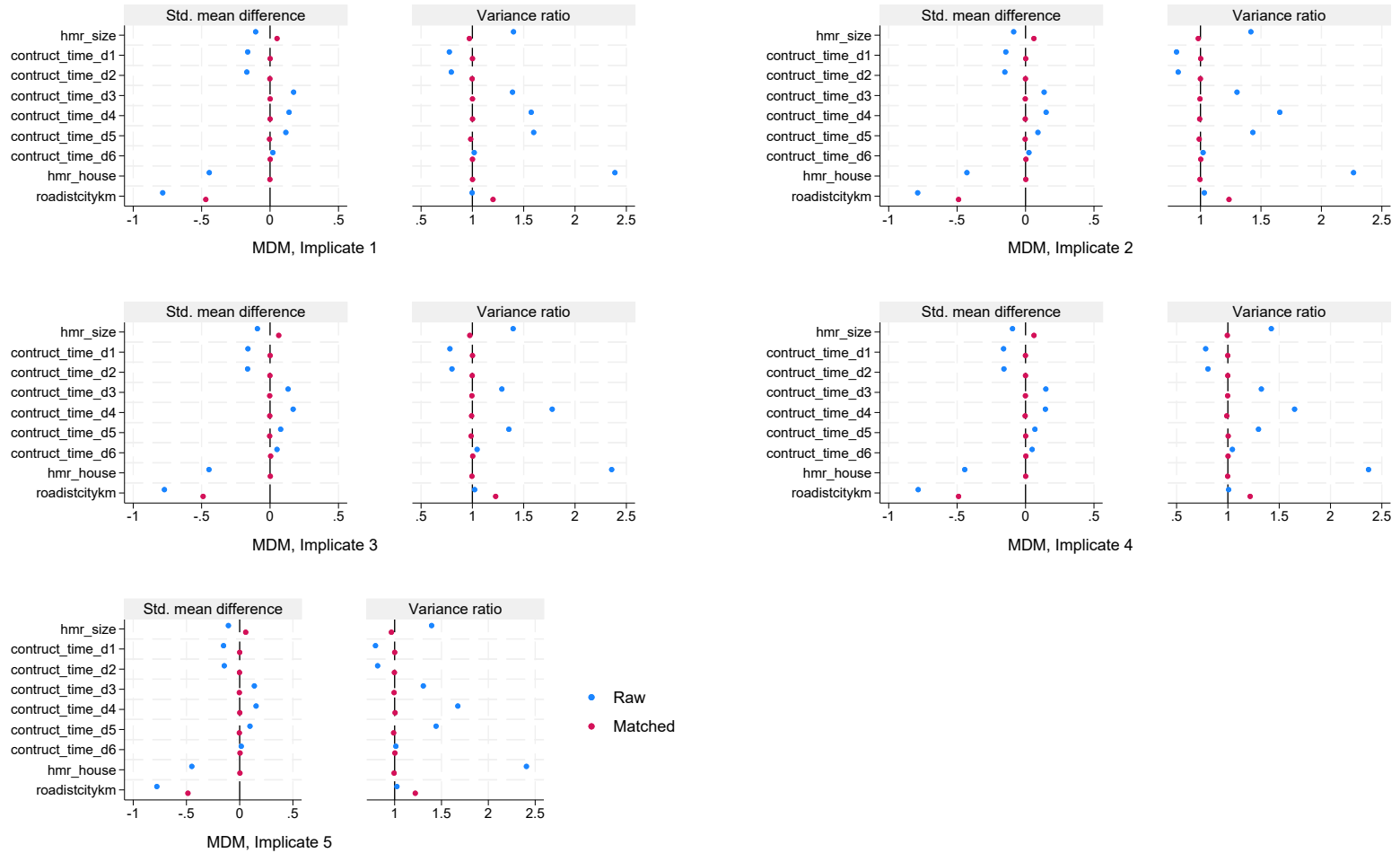


Figure 20: Diagnostics for properties less than 5 km away from the border - MDM



A.1.3 Results using different methods

Table 10: Border effect (ATE) using different matching method and distance from the border

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		3 km			4 km		5 km		
	NN	Kernel	MDM	NN	Kernel	MDM	NN	Kernel	MDM
ATE	0.723*** (0.057)	0.760*** (0.050)	0.700*** (0.043)	0.763*** (0.055)	0.766*** (0.045)	0.757*** (0.043)	0.779*** (0.048)	0.789*** (0.040)	0.793*** (0.030)
Observations									
Minimum	648	648	648	793	791	791	1121	1121	1121
Maximum	660	648	648	793	807	791	1132	1121	1121

Estimates refer to matching without regression adjustment.

Pooled standard errors across implicates are presented in parentheses using [Rubin \(1996\)](#); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Overall, the results suggest that kernel matching tends to yield slightly higher ATE estimates with smaller standard errors compared to nearest-neighbour matching across all distances. Additionally, the estimated standard errors for the ATE using MDM are the smallest, followed by kernel matching. Standard errors provide information about the precision of the estimates, with smaller standard errors indicating greater precision.

A.2 Regression Discontinuity Design

As a complementary robustness exercise, we estimate a geographic regression discontinuity specification using distance to the Luxembourg border as the running variable. The RD estimand is the local discontinuity in expected log property values at the border. This estimand differs from the matching ATE reported in the main analysis, which averages the quality-adjusted difference over properties within a 3–5 km strip and over the region of common support. Moreover, because observable property characteristics and residential composition may themselves change at the national border, the continuity assumption underlying a causal geographic RD is difficult to establish in our setting. We therefore regard the RD estimates as complementary evidence on the local price discontinuity.

In particular, for units within bandwidth h , we estimate the following equation,

$$Y_i = \alpha + \tau \mathbf{1}[D_i \geq 0] + \beta_1 D_i + \beta_2 D_i \cdot \mathbf{1}[D_i \geq 0] + X_i' \delta + \varepsilon_i,$$

where the outcome Y_i is the $\log(\text{price})$, the same as in the main text; D_i is the running variable defined as $D_i > 0$ if the dwelling is inside Luxembourg and negative otherwise; X_i is the set of covariates used in the PSM (hmr size, hmr type, road distance to Luxembourg city centre, dummies for hmr age, border segment dummies); τ is the Luxembourg price jump.

The results in the tables below have been calculated on the restricted sample used in the PSM considering

dwelling within a 4km or 5km strip.

Table 11: RD with predetermined covariates for precision 4km-strip

	(1)		(2)		(3)		(4)		(5)	
	RD imp1		RD imp2		RD imp3		RD imp4		RD imp5	
Conventional	0.576***	(0.104)	1.051*	(0.467)	0.786*	(0.322)	0.750*	(0.339)	0.760**	(0.240)
Bias-corrected	0.684***	(0.104)	0.905	(0.467)	0.652*	(0.322)	0.582	(0.339)	0.610*	(0.240)
Robust	0.684***	(0.204)	0.905	(0.471)	0.652*	(0.286)	0.582	(0.437)	0.610*	(0.279)
Observations	791		796		793		807		797	

Standard errors in parentheses

Notes: Covariates include: HMR size, HMR house dummy, road distance to Luxembourg city, HMR age classes, Border segment dummies
Clustered SEs by border-segment. RD uses triangular kernel and CCT bandwidth.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: RD with predetermined covariates for precision 5km-strip

	(1)		(2)		(3)		(4)		(5)	
	RD imp1		RD imp2		RD imp3		RD imp4		RD imp5	
Conventional	0.609***	(0.076)	0.631*	(0.254)	0.555**	(0.187)	0.459	(0.271)	0.721**	(0.247)
Bias-corrected	0.728***	(0.076)	0.693**	(0.254)	0.611**	(0.187)	0.537*	(0.271)	0.867***	(0.247)
Robust	0.728***	(0.140)	0.693	(0.355)	0.611*	(0.268)	0.537	(0.321)	0.867***	(0.260)
Observations	1121		1124		1123		1132		1125	

Standard errors in parentheses

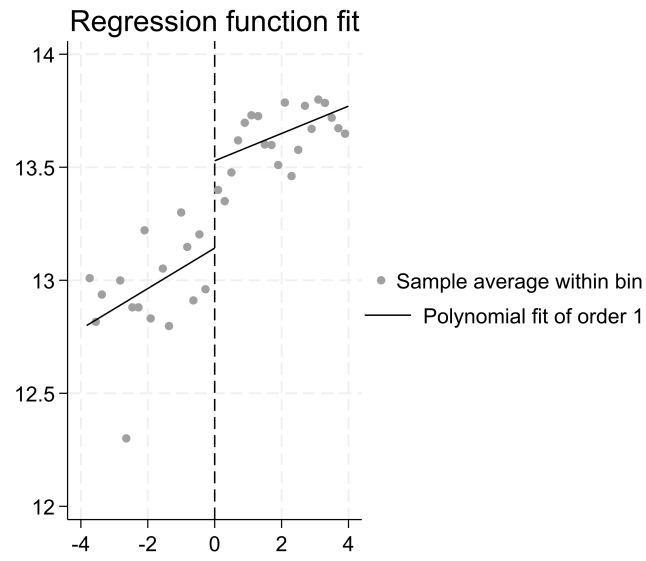
Notes: Covariates include: HMR size, HMR house dummy, road distance to Luxembourg city, HMR age classes, Border-segment dummies
Clustered SEs by border-segment. RD uses triangular kernel and CCT bandwidth.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Diagnostics & robustness

Figure 21 provides an additional descriptive check on the local price-distance relationship. Within the 4 km strip, the fitted slopes of log property values with respect to distance from the border are similar on the two sides. This pattern is consistent with similar local price gradients, but it does not establish continuity of potential outcomes at the border and is not used as a justification for the matching design.

Figure 21: RD plot for dwellings within a **4 km** strip from the border



Note: Plot for implicate 1. Plots for other implicates are similar.



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