Mandatory Disclosure and Housing Market Dynamics

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Abstract

This paper studies how mandatory disclosure of energy performance affects housing market outcomes, using the 2021 reform that made Energy Performance Certificate (EPC) ratings legally binding and visible in all real-estate advertisements in France. Leveraging staggered implementation across neighboring countries and rich microdata on property listings, I combine quasi-experimental and market-wide evidence to study the effects of energy performance disclosure on housing prices.

The results reveal a selective and uneven response to disclosure. At the France–Belgium border, mandatory disclosure induces a large and persistent price penalty of around 10 percentage points for energy-intensive dwellings, while prices of energy-efficient and average-performance properties remain largely unchanged. At the national level, the capitalization of disclosed energy performance is modest: energy-efficient houses command only small premia of about 3 percentage points relative to balanced dwellings, with no corresponding effects in the apartment market a few years after the introduction of the policy. By contrast, energy inefficiency is consistently penalized across property types, with price discounts of roughly 2 percentage points for apartments and 3 percentage points for houses relative to energy-balanced properties. Most strikingly, and contrary to the prediction of full unraveling, non-disclosure persists and is rewarded; listings without an EPC rating command a persistent premium of roughly 6 percentage points in the apartment market several years after the reform.

These findings indicate that mandatory disclosure does not simply reveal latent quality but reshapes strategic behavior in markets with heterogeneous preferences and informational frictions. The results challenge standard disclosure models and highlight how transparency policies can induce selective penalization and strategic non-compliance rather than full information revelation. The paper discusses implications for environmental policy design, housing affordability, and the distributional consequences of climate regulation.

JEL Code: C21, R31, Q48, D83, R38, H23, C52

1 Introduction

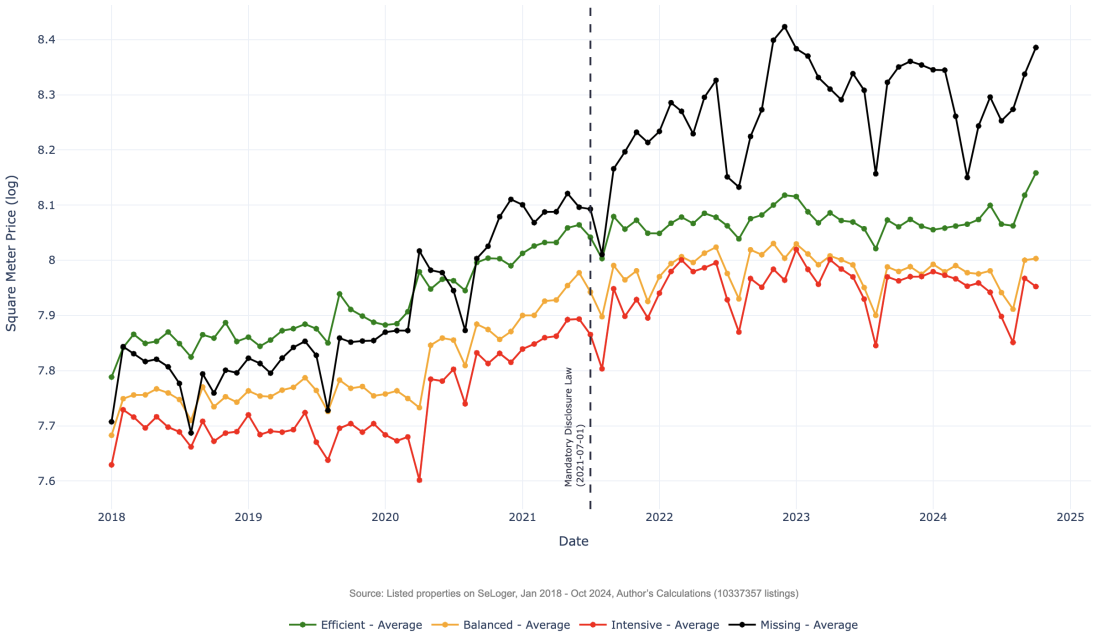
Despite sustained efforts to decarbonize the European economies, the housing sector remains one of the largest sources of national energy consumption and carbon emissions. Residential buildings account for nearly 30% of final energy consumption in France and approximately 40% across the European Union[1]. They are responsible for around 10% of France's total greenhouse-gas emissions and about 50% of the EU's overall emissions.[2]. Equally pressing is the phenomenon of energy precarity: across the EU, between 8% to 16% of the population may be classified as "energy poor" depending on the indicator used.[3] In France, many households continue to struggle with high energy bills and inadequate thermal comfort due to poorly insulated dwellings and inefficient energy systems. This dual challenge, both environmental and social, is deeply intertwined: energy-inefficient housing not only undermines France's climate objectives but also exacerbates social inequalities by trapping low-income households in energy-poor conditions. Against this backdrop, the introduction of mandatory disclosure of dwelling energy performance can appear as a useful policy lever (Gillingham, Newell, and Palmer 2009). By requiring transparent reporting of energy efficiency through standardised metrics, both at the national and European level, policymakers aim to make the energy quality of housing visible and understandable to market participants. Beyond simple transparency, such disclosure plays an essential educational role: it helps households and buyers grasp what constitutes an energy-efficient dwelling, reducing the so-called "energy-efficiency gap" as described by Gerarden, Newell, and Stavins 2017 and Allcott and Greenstone 2012: how different performance classes translate into real-world energy costs, and why renovation investments matter. When citizens can clearly interpret these ratings, energy performance becomes not just a technical indicator but a meaningful factor shaping housing choices, market value, and ultimately the collective transition toward low-carbon living. (Walls et al. 2017, Houde and Myers 2019).

Aiming to achieve carbon neutrality by 2050, governments have implemented mandatory disclosure of energy performance scores as a key mechanism to stimulate investments in energy-efficient property upgrades[4]. This approach reflects a broader policy trend in which information disclosure is used to empower consumers to make better-informed decisions in markets where product quality (in this case, energy efficiency) is not immediately apparent through other information mechanisms. While some details in property listings, such as the year of construction, heating system, or insulation type, can offer indirect clues about a property's energy performance, relying on these elements to assess efficiency is far from straightforward. The relationship between such features and actual energy performance is often complex and context-dependent, making inference uncertain. Moreover, these pieces of information are not always accurately or consistently reported in listings, which further limits buyers' ability to form a reliable or systematic understanding of a property's energy quality in the absence of an explicit EPC score (Gillingham, Newell, and Palmer 2009, Hunt Allcott 2017, Gerarden, Newell, and Stavins 2017).

Policymakers often regard these disclosure mandates as a cost-effective and less intrusive alternative to traditional regulatory interventions, intended to improve market transparency and efficiency. The central premise is that by revealing the energy performance of properties, the market should naturally establish a pricing hierarchy, rewarding energy-efficient buildings with higher values and discounting less efficient ones. Ideally, this price differentiation encourages property owners to invest in improving their buildings' energy performance as they fear being discounted by the market. Yet, in reality, the effects of such mandatory disclosure policies have proven to be more complex and varied than initially expected (Winston 2008; Loewenstein, Sunstein, and Golman 2014; Ho, Ashwood, and Handan-Nader 2019; Myers, Puller, and West 2022).

1. Eurostat Energy Balances and EEA Greenhouse Gas Inventory, 2023
2. "Rénovation performante des logements: une condition nécessaire pour atteindre les objectifs climatiques,", ADEME press release, 23 May 2024
3. "Who's energy poor in the EU? It's more complex than it seems", European Commission, Joint Research Centre, news release, 25 September 2024
4. We provide examples of these energy performance scores in Figure 3, showing two different EPC ratings: one from Immoweb, the main property listing platform in Belgium, and another from SeLoger, the leading platform in France.

Figure 1. Average Log of squared meter listed price per energy consumption level (full sample)



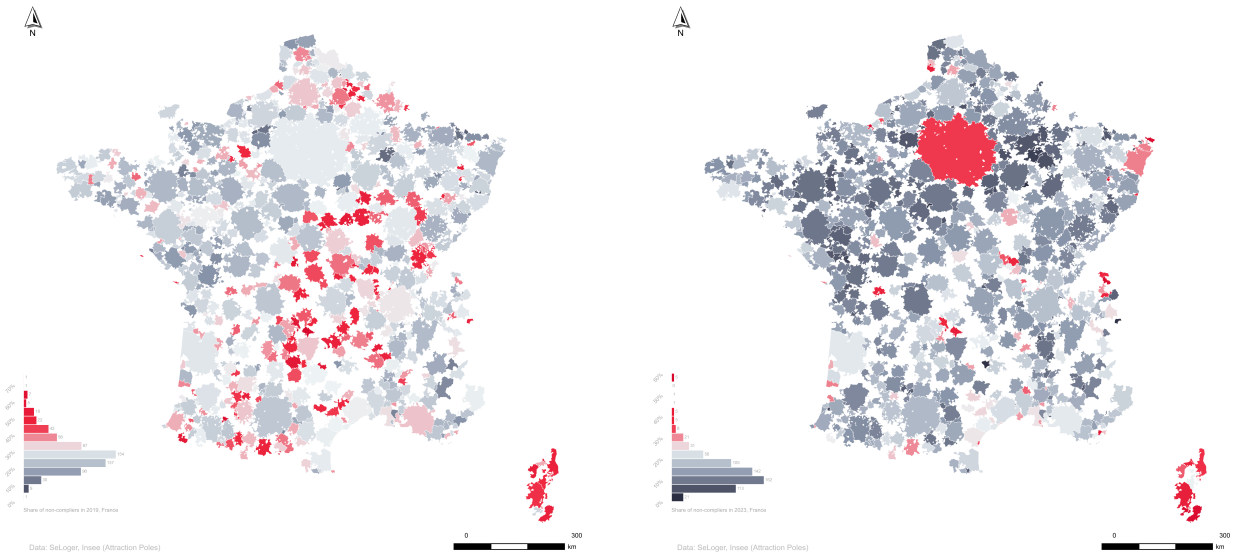
Note: The figure reports monthly averages of the logarithm of listed prices per square meter by energy consumption category (Efficient, Balanced, Intensive, and Missing) for the full sample from January 2018 to October 2024. The vertical dashed line indicates the introduction of mandatory energy performance disclosure in July 2021.

The central theory of disclosure relies on a key phenomenon known in the literature as the unravelling phenomenon, first developed by Grossman 1981 and Milgrom 1981. Under certain assumptions, full voluntary disclosure should occur even in the absence of regulatory mandates. The logic is straightforward: if sellers possess private information about a property or characteristic that can be credibly disclosed, rational observers will interpret any failure to disclose as evidence of the worst possible value. Anticipating this, even those with moderately unfavorable information have an incentive to disclose to distinguish themselves from those with the very worst outcomes. This chain reaction continues until all private information is revealed, leading to complete transparency, an equilibrium in which voluntary disclosure dominates. Since the unravelling process already predicts full disclosure when conditions are ideal, any policy that mandates it becomes redundant or counterproductive.

A preliminary analysis of the platform data reveals substantial spatial heterogeneity in disclosure behavior: certain areas consistently provided comprehensive energy information, while others disclosed very little, both prior to and following the implementation of mandatory disclosure requirements (see Figure 2). This spatial heterogeneity may also reflect heterogeneous preferences toward energy performance, as northern regions appear more inclined to disclose energy information than their southern counterparts under strict mandatory disclosure. Such a pattern could indicate that local market dynamics, climatic conditions, and social norms influence how energy efficiency is valued and communicated. For instance, in colder northern areas, where energy consumption for heating constitutes a significant share of household expenditure, both sellers and buyers might place greater emphasis on energy performance as an informative and market-relevant attribute. In contrast, in the south, where energy costs may be perceived as less burdensome, the incentive to disclose or seek detailed energy data might be weaker. In addition, market tension (tightness) in local housing markets can shape disclosure incentives: in high-demand, supply-constrained areas sellers may face weaker pressure to provide complete information, since properties sell quickly even with limited disclosure, an interpretation consistent with the Paris cluster, which exhibits comparatively low disclosure despite strong demand. Together, these variations suggest that spatial patterns of disclosure not only capture compliance behavior but also reveal deeper regional differences in the perceived importance and economic salience of energy performance. Moreover, Figure 1, which illustrates the evolution of the logarithm of average listed prices per square meter in France, suggests that the market had already internalized an energy efficiency price gradient (energy-efficient properties were listed at higher prices

than balanced or energy-intensive ones) even before disclosure became compulsory. Strikingly, properties listed without an energy performance score were priced similarly to energy-efficient ones, directly contradicting the classic unraveling hypothesis. This price gap appears to have widened further after the introduction of mandatory disclosure.

Figure 2. Spatial variation in energy disclosure rate across INSEE clusters and over time.



(a) Properties up for sale in 2019

(b) Properties up for sale in 2023

Note: Each polygon is an INSEE "attraction pole" cluster. Shading shows the share of for-sale listings with missing energy information (non-disclosure) in that cluster for the given year. Colors are centered on the national median at a given year (light tones): red = higher non-disclosure / lower compliance, gray = lower non-disclosure / higher compliance. The small histogram summarizes the distribution of cluster rates in each year. Source: SeLoger listings; INSEE attraction-pole geography.

Even though these stylized facts seem surprising, the theoretical prediction that all sellers should disclose relevant information ("the unraveling result") relies on several restrictive conditions (defined in Dranove and Jin 2010) that rarely hold in reality. The classic model assumes that properties differ only along a single, easily defined dimension of quality, that sellers possess full and private knowledge of their property's true quality, and that providing this information is costless. It also presumes a market structure with either perfect competition or monopoly, meaning there are no strategic interactions among sellers. Furthermore, it assumes that all buyers value higher quality (in this case, better energy efficiency) and are homogeneous in preferences and financial capacity, that they form rational expectations about homes without disclosed EPC ratings, and that the overall distribution of property quality is publicly known (e.g. Milgrom and Roberts 1986; Fishman and Hagerty 2003; Li and Shi 2017; Myers 2020; Myers, Puller, and West 2022).

If the central theorem of unraveling is true, then it means the market structure should naturally lead in a significant decrease in price for properties displaying the worst labels (the energy-intensive ones - F & G) and most importantly, that those properties not displaying their energy performance score. In reality, the housing market rarely satisfies these conditions. Providing an energy performance score can involve implicit or administrative costs. Sellers may adjust their disclosure strategies in response to neighboring properties, and buyers differ considerably in their motivations (some prioritizing lower carbon emissions while others remain indifferent), as well as in their knowledge and willingness to pay for greater energy efficiency.

This paper seeks to evaluate the extent to which the theoretical prediction of full information disclosure holds when confronted with empirical evidence from real housing markets. In particular, it investigates whether sellers respond to mandatory transparency requirements in a manner consistent with economic theory. Specifically, whether the unravelling result on prices emerges once mandatory disclosure of energy performance is enforced. To address

this question, the study exploits a natural experiment that unfolded at the European level, focusing on the 2021 regulatory reform in France that required all property listings to display their Energy Performance Certificate (EPC) rating in listed advertisements. This policy change combined with the unique vantage point offered by SeLoger's and Immoweb's comprehensive listing data, provides a rare opportunity to observe how market participants adapt when a major source of asymmetric information is suddenly made public and standardized across listings. By examining this shift, the paper aims to assess not only whether disclosure became more widespread, but also how the newly available information was reflected in property prices, thereby testing the core mechanisms underlying theories of information unraveling and market efficiency. Finally, beyond pricing and disclosure behavior, the paper draws out the policy relevance of the reform by discussing its welfare and equity implications, particularly the possibility that the reform intensifies income-based sorting and generates eviction effects, whereby lower-income households are pushed out of (or prevented from accessing) more energy-efficient dwellings due to the price surge of such properties.

2 Empirical Setting

The Energy Performance Certificate (EPC), introduced as part of the European energy legal framework, aims to standardize energy efficiency assessments across buildings. It provides a graded label (A to G) reflecting energy consumption and greenhouse gas emissions, enabling buyers and tenants to evaluate a property's *"green value"*. The system identifies energy-intensive homes (F and G labels), which are now subject to strict regulations to promote energy savings and meet climate objectives. The EPC contributes to the broader goals of reducing carbon footprints and promoting sustainable housing, aligned with *the European Green Deal*.

Since its implementation in 2002[5], the EPC has undergone significant evolution, with divergent trajectories in France and Belgium. France introduced EPC disclosure in 2006, gradually increasing its rigor. Key milestones include the mandatory inclusion of EPC information in property listings in 2011 and substantial reforms in 2021[6], which introduced stricter calculation methodologies and penalties for non-compliance. The French *"Climate & Resilience"* Law of 2020 further intensified these efforts, implementing a phased prohibition of poorly rated properties (e.g., banning the rental of G+ homes from 2023 and F homes by 2028). Subsidies and mandatory energy audits further encourage renovations for low-performing properties.

In Belgium, EPC disclosure started regionally in 2009 (Flanders) and 2011 (Wallonia) but achieved full implementation earlier than France with stricter requirements in 2015. Belgium enforced higher penalties and broader visibility for EPC ratings earlier in the policy timeline, resulting in a faster adaptation of the real estate market. This divergence highlights the differences in enforcement intensity and regulatory timelines, creating distinct impacts on property valuation and housing market dynamics.

2.1 Data

We build our empirical strategy on two complementary datasets of residential real-estate listings from France and Belgium. First, we use microdata from SeLoger (France) covering properties listed by real-estate agencies across metropolitan France from 2018 to 2024. The dataset contains 10 337 357 listings observed at daily frequency spanning 34 900 municipalities. Second, to support cross-border analyses, we construct a border sample combining listings from SeLoger and Immoweb (Belgium) for municipalities located in regions adjacent to the Franco–Belgian frontier. This border sample covers 5 225 municipalities and includes 765 304 listings, of which 489 794 (64%) are located in France and 275 510 (36%) in Belgium. SeLoger and Immoweb are two leading online listing platforms in their respective countries. Because listings are predominantly posted by professional real-estate agencies, the information is comparatively standardized and less prone to measurement error than purely user-generated listings.

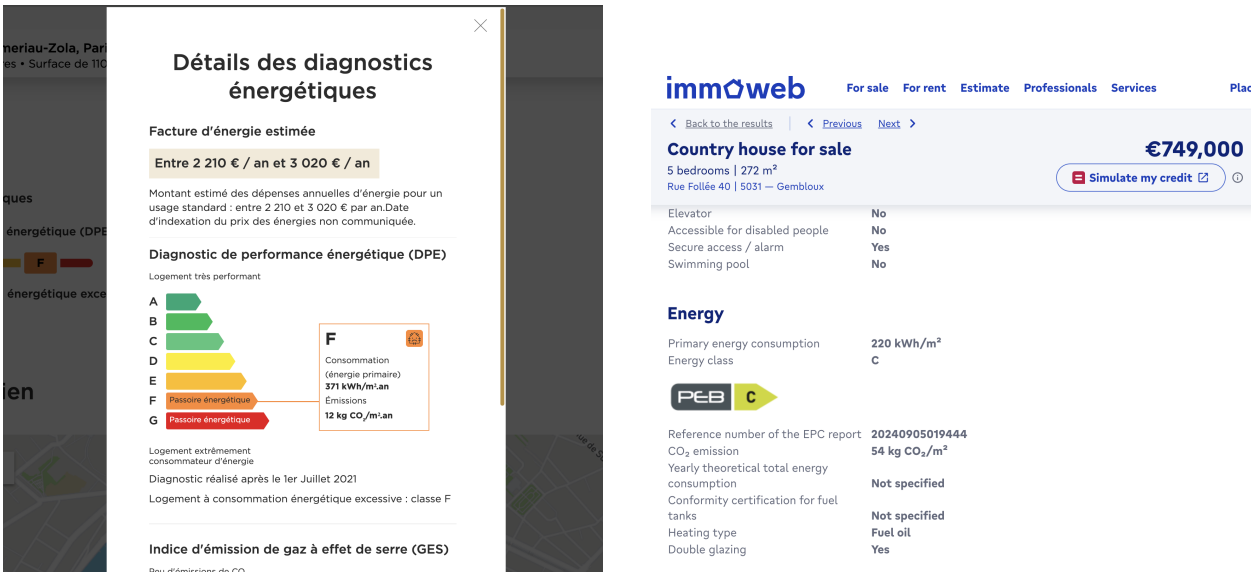
For each listing, we observe detailed property characteristics. Core variables include the advertised asking price, total habitable floor area (m^2), and room counts (e.g., bedrooms and bathrooms). We also observe a rich set of amenities and comfort indicators (e.g., heating system, building services, location at the address). Importantly for

5. Directive 2002/91/EC of the European Parliament and of the Council of 16 December 2002 on the energy performance of buildings. (The original EPBD)

6. Regulation (EU) 2021/1119 of the European Parliament and of the Council of 30 June 2021 establishing the framework for achieving climate neutrality and amending Regulations (EC) No 401/2009 and (EU) 2018/1999 ('European Climate Law') (OJ L 243, 9.7.2021, p. 1).

our research design, the data include energy-performance information: the Diagnostic de performance énergétique (DPE) label in France and the Performance Énergétique des Bâtiments (PEB) label in Belgium. These labels provide comparable signals of energy efficiency at the dwelling level (see Figure 3)

Figure 3. Sample of Energy Performance Score on SeLoger (France)and Immoweb (Belgium)



(a) DPE (SeLoger)

(b) PEB (Immoweb)

Note: The figure provides examples of how energy performance information is displayed on the two major listing platforms used in our study. Panel (a) shows the French Diagnostic de performance énergétique (DPE) label as presented on SeLoger, while Panel (b) displays the Belgian Performance énergétique des bâtiments (PEB) label as shown on Immoweb.

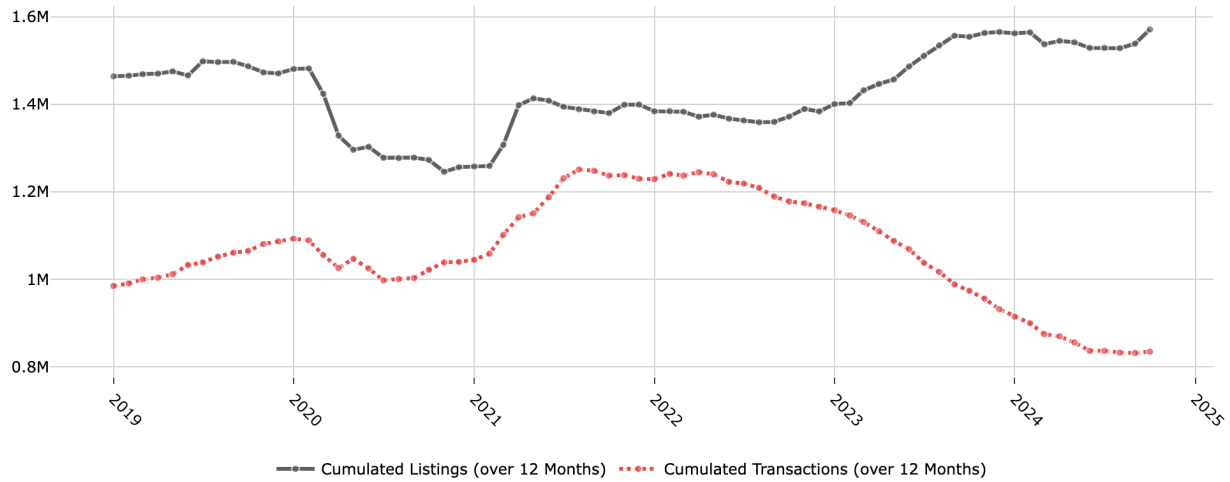
Finally, we employ the *World Administrative Boundaries* dataset, which provides globally consistent delineations of administrative units at multiple hierarchical levels, countries, regions, and subnational divisions (e.g., states, provinces, and municipalities). For the Franco–Belgian frontier, the dataset supplies precise geographic coordinate sequences that define the international boundary, enabling accurate spatial referencing in the vicinity of the border.[7]

2.2 Descriptive Statistics

- ***Representativeness.*** We benchmark the platform's coverage against independent market statistics and consider the economic incentives governing listing behavior. First, we use the national transaction volumes reported by the French notaries as an external benchmark for assessing the scale of the residential property market. Between 2019 and 2024, SeLoger consistently reported a larger number of property listings than the volume of completed transactions recorded by notaries. In 2024, for instance, SeLoger displayed over 1.5 million listings, while the notaries documented approximately 837 000 transactions (see Figure 4). This comparison is pertinent as it provides an indication of SeLoger's market coverage. While not all listings on the platform result in a sale, the persistent gap between listings and transactions suggests that SeLoger reflects a significant portion of the properties available for sale at any given time. The exposure ratio (the ratio of listings to transactions), which consistently exceeds 1, reinforces this interpretation, indicating that SeLoger consistently lists more properties than are actually transacted. As such, SeLoger offers a reasonably accurate reflection of the broader market.

7. Opendatasoft. (2024). World Administrative Boundaries Dataset. Retrieved from *https://public.opendatasoft.com/explore/dataset/world-administrative-boundaries/export*

Figure 4. Cumulated Listings and Transactions in the French Residential Market (2019-2024)



Sources: De-duplicated listings, SeLoger France (authors' own computations), Real Estate Reference Database, French Notaries – ADSN, DGFiP (MEDOC) - (Insee computations).

Second, the structure of the housing market suggests that major online platforms capture a large fraction of properties offered for sale. Because the residential market operates through decentralized search, sellers and real-estate agents face strong incentives to make properties visible across multiple channels to reduce search frictions and increase the likelihood of a match. Given the negligible marginal cost of posting a listing[8] on an additional portal, standard search-and-matching reasoning predicts extensive cross-platform duplication. Consequently, large national portals like SeLoger tend to host listings for a wide range of properties circulating on the market, even if they do not observe the entire stock. Third, listings on these platforms are entirely published by certified real-estate agents, rather than private individuals. This institutional feature implies a relatively homogeneous level of professional intermediation, standardized listing practices, and systematic use of online portals as the primary marketing channel. As a result, the platform data are well suited to capturing the segment of the market corresponding to professionally intermediated transactions, which constitutes the dominant mode of housing sales in France.

Importantly, to avoid overstating coverage due to multi-platform posting behavior, we implement a deduplication procedure that consolidates repeated observations of the same property. Listings are matched and merged based on location, timing, and key structural characteristics to ensure that each property appears only once in the analytical dataset. This step reduces noise arising from seller or agency multi-homing and yields a sample that more accurately reflects the underlying set of distinct dwellings offered for sale.

Finally, the properties advertised on these platforms are expected to primarily serve as primary residences rather than secondary or occasional dwellings. According to INSEE, primary residences account for more than 80% of the French housing stock in recent years[9], a share that has remained remarkably stable over time. While the platform does not observe the entire universe of dwellings, its focus on properties actively brought to the market by professional agents makes it highly likely that the listings predominantly correspond to housing intended for owner-occupiers.

- ***France-wide SeLoger sample.*** Across both the apartment and house markets, observable housing characteristics reported in Table 1 and 2 exhibit clear and intuitive differences across energy consumption categories that were already present prior to mandatory disclosure and remain largely stable thereafter.

8. Under the Loi Hoguet (Loi n° 70-9 du 2 janvier 1970), real-estate agents are prohibited from receiving any payment or commission prior to the successful completion of a transaction. This rule implies that agents bear the upfront cost of marketing and advertising a property, while remuneration occurs only if a sale takes place. As a consequence, the marginal cost of placing a listing on an additional online portal is extremely low, encouraging agents to diffuse each property across multiple platforms to maximize the probability of a match. This institutional feature reinforces the expectation, grounded in standard search-and-matching models, that major portals such as SeLoger capture a broad share of properties brought to market.

9. Insee; Ministry for the Ecological Transition and Territorial Cohesion, Statistical Data and Studies Service (SDES); Annual estimates of the housing stock as of January 1, 2023.

Efficient dwellings are systematically newer and better documented. In both markets, they are disproportionately built after 2004 and display lower rates of missing structural information. Balanced dwellings occupy an intermediate position, spanning a wide range of construction vintages and showing moderate prices and sizes. Intensive dwellings are concentrated among older housing stock and smaller units, consistent with poorer energy performance being correlated with age and quality.

The Missing category (i.e. listings published without an EPC score) stands apart in its observable characteristics. These listings exhibit high rates of missing construction-year and structural information, alongside intermediate price levels for houses and the highest average price per square meter among all categories. For these listings, energy performance is difficult to infer from observable characteristics alone.

In the house market, the composition of energy categories is relatively stable. In the pre-treatment period, Balanced houses account for 47% of listings, followed by the Missing category (26%), Efficient houses (19%), and Intensive houses (8%). After mandatory disclosure, these shares change only modestly: the share of Efficient houses increases to 23%, and the share of Intensive houses rises to 12%, while the share of Missing houses declines to 17%. Importantly, the Balanced category remains essentially unchanged at 47%. These movements are consistent with a limited reclassification of listings once energy information becomes available, rather than a structural change in the composition of houses brought to market. This pattern is consistent with disclosure primarily reducing informational opacity, by reallocating some listings out of the Missing category, without inducing largescale re-sorting across energy groups.

The apartment market tells a different story. Prior to disclosure, Balanced apartments account for the largest share of listings (about 44%), followed by Missing units (around 32%), Efficient apartments (19%), and Intensive ones (5%). In the post-treatment period, the share of Balanced apartments declines substantially to 38%, while the shares of Intensive and Missing apartments increase to 8% and 35%, respectively, and the share of Efficient units remains relatively stable at 19%. The distribution of energy performance categories remained largely unchanged, suggesting that compliance with the disclosure requirement is largely ineffective in the apartment market.

Despite these pronounced cross-sectional differences, comparisons between pre- and post-treatment periods reveal no evidence of structural re-sorting induced by mandatory disclosure in either the apartment or the house market. Within each energy category, post–pre differences in discrete characteristics (such as construction vintages, room counts, or bathroom distributions) are small, heterogeneous, and largely offsetting. Continuous variables such as surface area, log price per square meter, and distance also change only marginally over time, with no systematic pattern across energy groups (see Tables 1 and 2). Importantly, this stability holds within energy categories, indicating an absence of treatment-induced compositional change.

At the same time, the strong and stable differences in observable characteristics across energy consumption categories indicate that energy performance was already partly predictable prior to disclosure. Even in the pre-treatment period, Efficient dwellings tend to be newer, smaller, and more expensive per square meter, while Intensive dwellings are older, smaller, and cheaper. These patterns persist with very similar magnitudes after disclosure. This suggests that mandatory disclosure did not create new sorting across housing types, but instead made existing information more explicit. In this sense, disclosure appears to reduce uncertainty about energy performance rather than fundamentally altering the composition of listings.

For the Missing category, however, the interpretation is more nuanced. The lack of a sharp post-treatment compositional change does not rule out strategic non-disclosure behavior. Because key covariates that are typically informative about energy performance (like construction vintage) are disproportionately unavailable, energy type remains difficult to infer for these listings. This creates scope for strategic hiding, in the sense that poorly energy-efficient properties may remain pooled within the Missing category precisely because their characteristics are weakly observed. While the data do not reveal a clear post-treatment shift toward observables typically associated with low energy efficiency, the persistence of informational opacity implies that such behavior may occur but cannot be directly identified using observable characteristics alone.

Overall, these descriptive statistics strengthen the credibility of causal interpretations based on post-treatment outcomes. Mandatory energy disclosure primarily operates as an information-enhancing policy, improving transparency where inference is feasible, while leaving the underlying structure of the housing market largely unchanged and leaving some residual opacity where information remains incomplete.

- ***Cross-border SeLoger–Immoweb sample.*** Across both houses and apartments, the descriptive statistics reported in Tables 3 and 4 show that France and Belgium differ systematically in several structural characteristics, yet these differences are remarkably stable over time and shrink substantially as we restrict attention to properties located close to the border. In the full >20km bands, Belgian houses are on average 45 m^2 larger than French houses (e.g., 172.27 m^2 vs. 128.12 m^2 in 2019; 169.65 m^2 vs. 123.73 m^2 in 2024), and apartments show similar gaps (roughly 25–30 m^2). These contrasts are essentially unchanged across 2019–2024, indicating that they reflect long-standing national building norms rather than shifting demand or supply conditions. However, once we move into the 5 km band, the cross-border gaps become much smaller: house size differences fall to roughly 40 m^2 while apartment differences shrink even more sharply to around 7–12 m^2 (e.g., 82.66 m^2 vs. 71.43 m^2 in 2019; 79.58 m^2 vs. 72.14 m^2 in 2024). This spatial convergence is consistent with the idea that settlements directly adjacent to the border share similar urban structures, land constraints, and housing stocks, making properties more comparable for buyers deciding between France and Belgium.

  A central pattern for identification concerns energy consumption, the dimension that determines the policy's treatment intensity. In contrast to the large differences in size or layout, energy-consumption levels are much more tightly aligned across the border, especially within narrow bands. For example, in the 5 km area for houses, average consumption differs by only 30–35 kWh/m^2 (Belgium 218–228 vs. France 191–212 across years), with gaps shrinking further in some years (only –5.9 kWh/m^2 in 2023). For apartments the convergence is similar: in 2019 5 km, the gap is –37 kWh/m^2, but by 2024 it is almost identical (–39.8 kWh/m^2), and in several mid-range bands the differences shrink close to zero. These magnitudes represent much smaller relative differences compared with size or layout and, crucially, place both French and Belgian properties into the same energy-performance categories under the regulatory schema. This also suggest that our design does not suffer from massive compositional change after the introduction of mandatory disclosure of energy performance in France in 2021.

  More importantly, once the sample is stratified by energy-consumption category, the remaining differences in structural attributes, especially building age, essentially disappear. Although Belgium exhibits slightly newer buildings in broader bands (for houses, e.g., 1981 vs. 1930 in 2019), conditioning on energy levels equalizes these differences: within each consumption bin the distribution of construction years aligns almost perfectly across countries. This is mechanically expected: energy labels encode both building vintage and renovation history, meaning that conditioning on consumption implicitly conditions on age. Since the policy is defined within energy-performance strata, this conditional convergence is precisely what matters for the identification strategy. In other words, within the strata where treatment is assigned, French and Belgian dwellings are already closely comparable in both energy use and age, the two variables most tightly linked to the policy's thresholds.

  The descriptive evidence points to a setting that is naturally well suited for credible causal inference. First, differences between the French and Belgian sides appear broadly stable over time, suggesting that persistent cross-country features, such as long-standing construction norms or institutional factors, are unlikely to generate spurious changes around the policy period. When these differences are effectively time-invariant, identification can hinge on changes over time rather than level gaps, which reduces imbalance risks by netting out fixed national characteristics instead of conflating them with the effect of the regulation. Second, observable imbalances shrink as the analysis focuses on locations increasingly close to the frontier, indicating strong local comparability in the immediate vicinity of the border and supporting the idea that properties on either side can serve as plausible counterfactuals within narrow spatial windows. Finally, examining outcomes separately by energy-consumption categories not only sharpens the interpretation of the regulation, but also aligns comparison groups more tightly along the very characteristics that govern exposure to the policy. Overall, the joint patterns of temporal stability and spatial convergence provide a compelling rationale for a border-based identification approach aimed at isolating the causal effect of the regulation.

3 Empirical Strategy

In this section, we outline the empirical strategy used to estimate the effect of energy efficiency information disclosure on home prices. Our approach is divided into two key steps.

First, we begin by exploiting the variation in the adoption of mandatory energy efficiency disclosure regulations between France and Belgium. These two countries, both part of the European Union (EU), transposed this

regulation into their national laws at different points in time: Belgium implemented the regulation in 2015[10], while France adopted it in 2021[11]. The EU's legal framework operates under a hierarchy of norms, meaning that EU directives must be transposed into national law by member states within a specified period[12]. Consequently, the staggered implementation of the energy efficiency disclosure regulation offers a natural experiment to estimate the causal effect of disclosure on home prices, particularly at the border between these two countries. By examining the local average treatment effect (LATE) at various points in time, we can identify the impact of mandatory energy efficiency disclosure on home prices, leveraging this unique temporal variation. Second, building on the insights from the local approach, we aim to extend our analysis to estimate the average treatment effect (ATE) across the entire country. This extension relies on a key assumption derived from the local treatment effect analysis at the border. In this second step, we will also assess the level of compliance with the disclosure regulation and examine premia to non-disclosure.

In both stages of our analysis, we will not only estimate the overall average effect of energy performance disclosure on property prices but also explore how this effect varies across the distribution of energy efficiency ratings. Because the EPC framework is based on discrete administrative categories rather than a continuous scale, we anticipate that the response of housing markets to information disclosure is inherently non-linear. The publication of energy performance information may alter buyer and seller behavior in ways that depend on the perceived salience and credibility of the rating. For instance, energy-efficient dwellings may benefit from a signaling premium once their favorable classification is made visible, whereas low-efficiency homes may experience a price discount reflecting anticipated renovation costs or reduced desirability. Homes with intermediate ratings could display more ambiguous responses, depending on local market composition and buyers' valuation of energy savings relative to other property characteristics.

Moreover, these heterogeneous effects are likely to reveal how disclosure policies interact with pre-existing market expectations. If the market had already priced in energy efficiency before mandatory disclosure, we might observe limited changes among high-performing dwellings but more pronounced adjustments among properties previously withholding information. Conversely, if disclosure increases awareness and comparability, it could strengthen the price gradient between efficient and inefficient properties. By systematically examining these differential effects across EPC thresholds, our analysis seeks to uncover not only the average policy impact but also the mechanisms through which information transparency reshapes the valuation of energy performance in the housing market.

3.1 Estimating the pure effect of mandatory disclosure of energy efficiency information at the border between France and Belgium

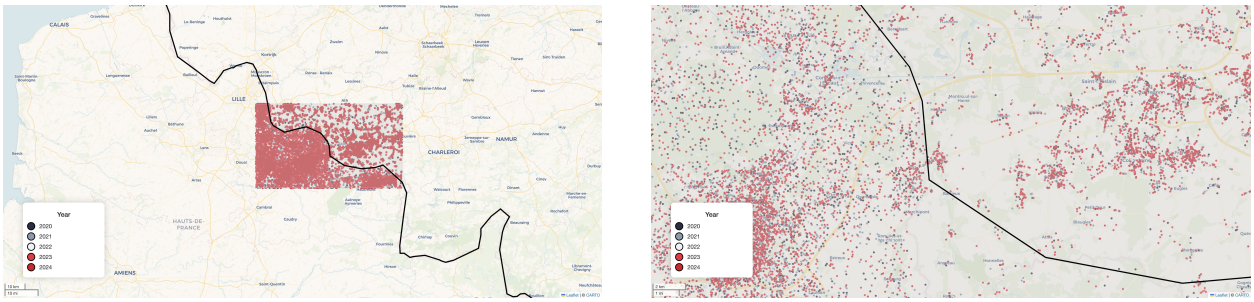
Our main research question revolves around understanding how the mandatory disclosure of energy efficiency information impacts housing prices. Specifically, we aim to examine whether revealing an Energy Performance Certificate (EPC) score influences the price at which properties are listed. Estimation of such effect is challenging because the regulation mandating the display of EPC scores on property listings was introduced uniformly across France on a specific date. Every property owner listing their property for sale is required since July 2021 to display a valid standardized EPC score in the add, which must be certified by an independent evaluator. This nationwide mandate complicates the task of establishing control and treatment groups for comparison.

To tackle this challenge, our initial approach will focus on the France-Belgium border. We will compare property listings from both sides, using Belgium (where the regulation is already in place) as the control group, and France (where the regulation is not yet implemented) as the treatment group. Our study will focus on listings published between 2019 and 2024, allowing us to explore the effects of the regulation just before and after its implementation in France. More specifically, we aim to leverage the discontinuous change in home prices at the border, alongside varying adoption patterns of mandatory energy disclosure, to identify causal effects on the real estate market. Between 2015 and 2021, France did not require mandatory energy disclosure, while Belgium did. We expect this

10. Ordonnance du 2 mai 2013 relative au Code bruxellois de l'air, du climat et de la maîtrise de l'énergie (CoBrACE), which entered into force on 1 January 2015 in the Brussels region and transposed the Directive 2010/31/EU on the energy performance of buildings.
11. Loi n° 2021-1104 of August 22, 2021 on fighting against climate change and strengthening resilience to its effects.
12. Both France and Belgium are EU member states, which means they are bound by EU law. Under the principle of the hierarchy of norms, EU regulations and directives must be transposed into national law within a specific timeframe. The energy efficiency disclosure regulation, part of the EU's broader climate and energy policy, was implemented at different times in these two countries. This regulatory divergence provides a quasi-experimental setup to assess the effect of energy efficiency disclosure on home prices.

to create a natural discontinuity in home prices only attributable to mandatory disclosure at multiple key levels of EPC scores, providing a valuable opportunity to study the impact of the regulation.

Figure 5. Spatial distribution of geo-localized listed properties over time



Note: The left panel shows a 70×40 km geographic buffer containing listings posted between 2019 and 2024, while the right panel provides a zoomed-in view of the same area. Each colored dot represents a property listed on SeLoger or Immoweb in a given year. For clarity, we plot only a small segment of the border here; however, in our inference exercise, we extend the analysis to the full border and use a larger buffer, as illustrated in Figure 6. Source: SeLoger/Immoweb listings, World Administrative Boundaries (France-Belgium)

Focusing on the border region offers clear advantages due to the expected quasi-random nature of the listings generating process around the border. The geographical boundary provides a distinct cutoff where property listings on either side can be directly compared, helping to isolate the effects of the regulation. The proximity to the border essentially determines the treatment assignment, listings on one side of the border are exposed to the regulation, while those on the other side are not. This setup mimics a randomized experiment, where the treatment assignment (the listing data generation process on platforms) appears to be quasi-random based on the location relative to the border. As a result, any discontinuity in the conditional distribution (or related features such as the conditional expectation) of housing prices, as a function of distance from the border, could be interpreted as evidence of a causal effect of mandatory disclosure. However, for this geographic discontinuity design to be valid, several assumptions must be met to ensure that the quasi-random nature of the assignment holds and the comparison between the two sides of the border is unbiased[13].

We identify three main threats to validity in the context of a traditional geographic RDD, each of which we will address. First, we anticipate that the discontinuous change in housing prices at the border may not be solely attributable to the mandatory disclosure of energy performance but could also be influenced by other time-invariant policies or regional differences. For instance, varying tax systems on either side of the border could affect sorting behavior, leading individuals to self-select into areas with more favorable tax policies, thus confounding the causal interpretation of the price gap. Second, this design relies on precise location identification based on self-reported addresses, which are not always consistently or accurately recorded in the data[14]. Third, the geographic RDD assumes that locations and covariates are randomly distributed along both longitude and latitude. This implies that covariate balance should hold both longitudinally (within a reasonable bandwidth, where distance from the border should not disrupt balance) and latitudinally, where the relative positioning of listings along the border should not affect balance. However, in our case, we expect significant latitudinal heterogeneity, as housing prices are influenced by amenities and major attraction points which are unevenly distributed along the border (e.g., large cities, attraction poles but also amenities on either side). While controlling for this heterogeneity is possible, it introduces high-dimensional challenges, particularly given the restricted sample we are working with (limited to a specific bandwidth around the border).

13. A detailed explanation of these assumptions can be found in Section 5.2 of the appendix, where we outline their motivation and implications in our design

14. Even when some address fields are missing, each listing still includes at least the municipality, which anchors the observation to a reliable approximate location. For records with incomplete or inconsistently reported address-level details, we do not default to a single point like a city centroid. Instead, we draw a random location within the city's polygon. This approach preserves the spatial distribution of listings within each municipality and avoids systematically pushing observations toward or away from borders, transport nodes, or other features. As a result, distance-based measures, particularly those used near administrative boundaries, remain unbiased. Further implementation details and robustness checks are provided in Appendix §5.3.

3.1.1 *Empirical Design. ML based Geographic Difference-In-Discontinuity*

Let the data be denoted by $\{W_{it}\}_{i\in[n],\, t\in[T]} = \{(Y_{it}, \Delta^*_{it}, Z_{it})\}_{i\in[n],\, t\in[T]}$, where $[n] = \{1, \ldots, n\}$ and $[T] = \{1, \ldots, T\}$. The sample consists of $n \times T$ independent and identically distributed observations drawn from the joint distribution of $W = (Y, \Delta^*, Z)$.

The outcome variable of interest, $Y_{it} \in \mathbb{R}$, is the natural logarithm of the listed price per square meter for property i at time t. The running variable is given by $\Delta^*_{it} \in \mathbb{R}$. Let Δ_{it} denote the distance between listing i and the border c at time t. We define the normalized distance as $\Delta^*_{it} = \Delta_{it} - \Delta_c$ so that $\Delta^*_{it} = 0$ corresponds to a listing located exactly on the border. While several distance metrics are considered, our primary specification employs the shortest *great-circle distance*[15] between the border and the listing location.

Finally, $Z_{it} \in \mathbb{R}^d$ represents a high-dimensional vector of covariates, which includes over 5,000 municipality fixed effects along with various property characteristics observed for listing i at time t.

Following Picchetti, Pinto, and Shinoki 2024 we consider two time periods[16], $t = 0$ and $t = 1$, with treatment determined by a threshold Δ_0 on the running variable Δ_i at $t = 0$. The treatment, defined as exposure to mandatory disclosure of energy performance, is introduced between $t = 0$ and $t = 1$ in the treated region (France, above Δ_0), while it is already in effect in the control region (Belgium, below Δ_0). Consequently, only some units are exposed to the treatment of interest at $t = 0$, and all units are treated by $t = 1$. If a pre-existing confounder arises from the discontinuity at Δ_0 (i.e., a time-invariant discontinuity in outcomes at $t = 0$), we refer to it as the *confounding treatment* (e.g., differences in regulatory or tax systems for instance). We indicate whether listings were *exposed to mandatory disclosure treatment* in period t with $D_{i,t} = 1$ and units that were already exposed to *mandatory disclosure treatment* with $D_{i,t} = 0$, where $D_{i,0} = 0$ implies *treatment* by the confounding policy and $D_{i,1} = 1$ implies treatment by the actual treatment of interest (mandatory disclosure).

Our objective is to identify the local causal effect of the treatment of interest, $D_1 = 1$, at the threshold $\Delta^* = 0$. To this end, we compare changes in outcomes between the pre- and post-treatment periods for units located near the cutoff, considering both treated and untreated groups. Under suitable assumptions, Picchetti, Pinto, and Shinoki 2024 show that this identification strategy is equivalent to analyzing the difference between multiple RDDs at multiple time periods.The estimand of interest at time t is given by:

$$\begin{cases} \tau^{\textit{RDDisc}}_{\textit{Without Adjust}}(t) & = \tau_t - \tau_{\text{baseline}}, \quad t \neq \text{baseline}, \\ \tau_t & = \lim_{\delta\downarrow 0} \mathbb{E}\left[Y_{it} \mid \Delta^*_{it} = \delta\right] - \lim_{\delta\uparrow 0} \mathbb{E}\left[Y_{it} \mid \Delta^*_{it} = \delta\right] \end{cases} \tag{Eq. 1}$$

By taking the difference between the two RDDs, we eliminate time-invariant confounding treatments and potential sorting effects that could otherwise generate spurious price differences across EPC scores at the border not attributable to the introduction of mandatory disclosure. Provided that no other policies are implemented at the border during the study period, the estimator $\tau^{\textit{RDDisc}}_{\textit{Without Adjust}}(t)$ identifies the local average treatment effect (LATE) of the policy of interest. This identification benefits from the quasi-random assignment induced by the discontinuity in the running variable while removing time-invariant confounding treatments at the border. To the best of our knowledge, within a reasonably short time window following the introduction of mandatory disclosure, no additional policies are expected to influence housing prices at the border.

Note: The black line traces the border segment used in the analysis. The shaded areas depict nested geographic buffers (bandwidths) of 5, 10, 15, 20, and 25 km around the border (see legend), with lighter shades indicating wider buffers. These alternative bandwidths are used to assess the sensitivity of our results to the choice of geographic window. Our chosen window corresponds to the data-driven optimal bandwidth obtained using Calonico, Cattaneo, and Farrell 2020.

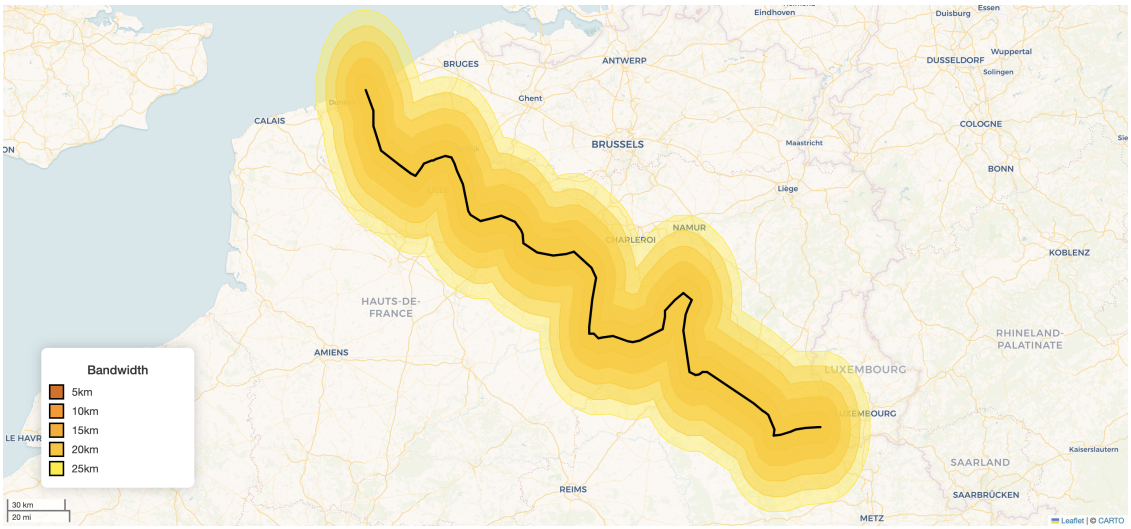
15. The great-circle distance is the shortest distance between two points on the surface of a sphere, accounting for the Earth's curvature. It can be computed using the Haversine formula:

$$d = 2r \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2\left(\frac{\Delta\lambda}{2}\right)}\right),$$

where r denotes the Earth's radius, ϕ_1 and ϕ_2 are latitudes, and $\Delta\phi$ and $\Delta\lambda$ are differences in latitude and longitude.

16. In practice, the framework extends to multiple periods. For clarity, we present the simplified two-period case, as the generalization is straightforward.

Figure 6. Multiple geographic buffer size (Bandwidth Selection)



The quasi-random assignment induced by the border requires us to limit our analysis to a narrow geographic buffer, typically a few kilometers around the border itself. Since we anticipate that the treatment effect will differ based on the energy performance of housing, it is essential to refine our analysis by dividing the housing market into three distinct categories: energy-efficient, energy-intensive, and energy-balanced properties. As discussed in the introduction, the policy goal is to establish a pricing gradient that reflects the varying energy performance of these properties. In order for the policy to meet its objectives, it must penalize energy-intensive properties to encourage improvement while ensuring that the premiums for energy-efficient properties are not so high as to cause displacement (i.e., eviction effects). At the same time, the policy should maintain enough of an incentive to encourage property owners to invest in energy renovations.

By analyzing these three categories, we effectively subset the dataset to capture the heterogeneous effects of energy performance disclosure at the border. This approach presents a significant challenge: by segmenting the dataset into distinct categories, we move into a high-dimensional analytical space where the number of available observations for each feature is reduced. As we narrow our focus to the three specific housing categories for a given bandwidth, the sample sizes within each group become smaller, which increases the potential for issues related to statistical power. With fewer observations for each subset, the likelihood of overfitting also rises, as the model may start to capture noise rather than meaningful patterns. While this finer categorization improves the precision of our analysis by allowing us to better understand the varying effects of energy performance, it also introduces a trade-off. The more granular the analysis, the more complex the model becomes, and this complexity must be weighed against the available data to avoid drawing misleading conclusions. Careful attention is needed to ensure that the model remains both robust and generalizable despite the reduced sample sizes in each category.

In this context, despite the absence of noticeable compositional shifts in observable characteristics according to Tables 3 and 4, it remains necessary to account for spatial heterogeneity and covariate adjustments[17] in our empirical specification. Specifically, in addition to property specific controls, we include controls for listing location to capture potential latitudinal and longitudinal gradients that may otherwise introduce confounding. Accounting for such spatial variation ensures that any estimated discontinuities are not spuriously driven by geographic clustering or regional market dynamics. These spatial variations are particularly challenging to account for, as they may influence housing prices and outcomes differently depending on the specific characteristics of each region and may not necessarily be time invariant. To address this, our strategy explicitly controls for both city location and property characteristics, given that the literature consistently identifies these factors such as proximity to amenities, local labor market conditions[18] and neighborhood quality[19] as key determinants of housing prices.

17. See Section 5.4 of the appendix for a more detailed description
18. Bayer, Ross, and Topa 2008; Bayer, Ferreira, and McMillan 2007
19. Chay and Greenstone 2005; Linden and Rockoff 2008; Ferreira and Wong 2020

However, the precise functional form through which these spatial attributes affect prices is generally unknown; for example, attraction poles related to labor market access or major amenities may have complex, nonlinear effects. Figures 7, 8 and 9 provide a conceptual illustration of spatial heterogeneity that may affect the validity of our regression discontinuity design. Each figure depicts hypothetical attraction poles (representing clusters of amenities, employment centers, or other geographically concentrated factors) that influence housing demand and, consequently, local price formation. Figure 8 illustrates a situation where attraction poles are distributed unevenly along the latitudinal axis, generating systematic north–south variation in property values. Figure 9 extends this to longitudinal heterogeneity, where overlapping zones of influence across the east–west dimension may produce localized price gradients. In a difference-in-discontinuities framework, latent spatial heterogeneity can bias estimates when the treatment cutoff coincides with underlying geographic gradients in housing prices. If areas on either side of the cutoff differ systematically in their spatial characteristics, such as proximity to amenities, labor market access, or regional growth trajectories and that these spatial patterns evolve differently over time, the estimated difference in discontinuities may partially capture spatial market dynamics rather than the causal impact of the policy itself. These figures therefore underscore the importance of controlling for geographic coordinates and regional characteristics to isolate the causal effect of energy performance from spatially driven price variation.

Figure 7. Uniform attraction pole distribution

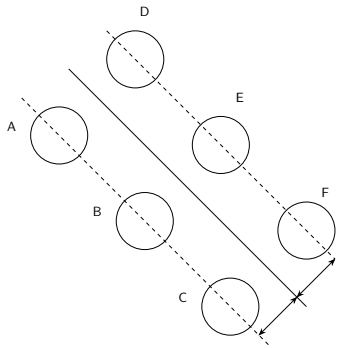


Figure 8. Latitudinal non-uniform attraction pole distribution

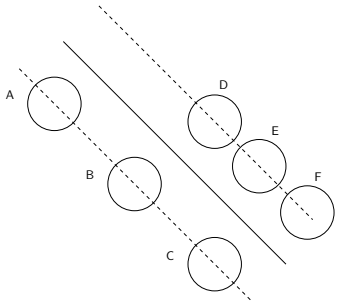
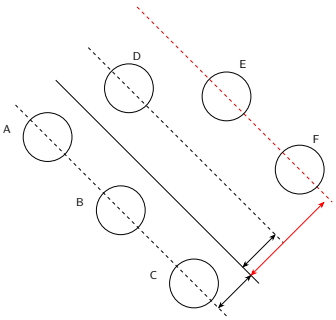


Figure 9. Longitudinally non-uniform attraction pole distribution



Note: Points A–F represent hypothetical attraction poles whose spatial influence may generate latent gradients in housing prices. In Figure 8, the uneven north–south positioning of A–F illustrates latitudinal variation, while Figure 9 depicts overlapping east–west zones of influence. These schematic patterns highlight how spatial heterogeneity can create systematic differences around the treatment cutoff, underscoring the need to control for geographic coordinates and regional characteristics in the empirical specification.

To remain agnostic regarding this functional relationship, we allow the data itself to inform the model, rather than imposing restrictive parametric assumptions. Moreover, in relatively small samples, controlling for a high-dimensional set of covariates such as multiple city locations and detailed property features can lead to overfitting when estimating the local linear RDD in the baseline objective function. This motivates the use of methods capable of flexibly modeling spatial heterogeneity while mitigating overfitting risks. Following Noack, Olma, and Rothe 2025, we allow for a flexible inclusion of control variables in high-dimensional settings by considering general outcome adjustments of the form $Y_{it} - \eta_0(Z_{it})$, where η_0 represents a potentially nonlinear function of the covariates Z_{it}. This approach enables us to account for complex, high-dimensional relationships between the outcome and covariates without imposing restrictive parametric assumptions. Assuming that $\mathbb{E}\left[\eta_0(Z_t) \mid \Delta_t^* = 0\right]$ is twice continuously differentiable in a neighborhood around $\Delta_{it}^* = 0$ for a broad class of functions η, different specifications of η_0 yield the same estimand for the adjusted RDD estimator at time t.

$$\begin{cases} \tau^{\text{RDDisc}}_{\text{With Adjust}}(t) & = \tau_t - \tau_{\text{baseline}}, \quad t \neq \text{baseline}, \\ \tau_t & = \lim_{\delta \downarrow 0} \mathbb{E}\left[Y_{it} - \eta_0(Z_{it}) \mid \Delta_{it}^* = \delta\right] - \lim_{\delta \uparrow 0} \mathbb{E}\left[Y_{it} - \eta_0(Z_{it}) \mid \Delta_{it}^* = \delta\right] \text{ for all } \eta_0 \end{cases} \tag{Eq. 2}$$

General Estimation Procedure. *ML Based Geographical Difference-in-Discontinuity*

1. *Data-Driven Bandwidth Selection.* We restrict the analysis to a subsample of the dataset $\{W_i\}_{i\in 1,\dots,n}$ by performing Data-Driven Bandwidth Selection for each time period t, as outlined in Cattaneo, Idrobo, and Titiunik 2024. Specifically, we consider only the listings within the geographical buffer defined by the maximum optimal bandwidth computed across the time periods under consideration. This is determined by the highest bandwidth, $h^* = \max(h_t)$ in kilometers, across all time periods t, resulting in the observed data set $\{W_i(h^*)\}_{i\in 1,\dots,n}$.

2. *K-Fold Splitting.* We perform K-Fold Cross-Validation by randomly splitting the dataset $\{W_i(h)\}_{i\in 1,\dots,n}$ into S folds of approximately equal size for each period t, where $S = 5$ in our case. The indices of the observations in each fold are collected in the sets I_s for $s \in 1,\dots,S$. For each fold s[a], we compute the estimator $\hat{\eta}_s(z) = \hat{\eta}_{z;\{W_i\}_{i\in I_s^c}}$, where I_s^c represents the set of indices corresponding to observations not included in fold s. This cross-fitting procedure ensures that the model is trained on data outside each fold, providing a more reliable and unbiased estimate of the treatment effect. We consider multiple class of estimator of η_0 calculated using only data from outside the sth fold allowing for various linear and nonlinear specifications: *Linear Regression*, *Random Forest*, *Grandient Boosting* and *Lasso Regression*

3. *Model-Specific Housing Price Adjustment.* For each model, in order to maximize the precision of the estimator $\hat{\tau}_t(h,\eta)$, we select η_0 that minimizes the variance. Specifically, following Noack, Olma, and Rothe 2025, we define η_0 as the average of the conditional means on either side of the cutoff:

$$\eta_0 = \frac{1}{2}\left(\mu_0^+(z_i) + \mu_0^-(z_i)\right), \quad \mu_0^*(z_i) = \mathbb{E}\left[Y_i \mid \Delta_i^* = 0, Z_i = z\right], \quad * \in \{+,-\}$$

   We then compute the residuals for each model specification[b] (i.e., housing prices adjusted for spatial effects and intrinsic property characteristics):

$$\tilde{Y}_i(h^*) = Y_i(h^*) - \hat{\eta}_{0s}(h^*, Z_i)$$

4. *RDD robust confidence intervals.* We then estimate τ_t by computing a local linear "no covariates" RDD estimator that uses the adjusted outcome $\tilde{Y}_i(h^*) = Y_i(h^*) - \hat{\eta}_{0s}(h^*, Z_i)$ for each time period t as the dependent variable, where $s(i)$ denotes the fold containing observation i. Specifically, estimate τ_t as:

$$\hat{\tau}_{\hat{\eta}(h^*)} = e_2^T \arg\min_{\theta\in\mathbb{R}^4} \sum_{i=1}^{n} K_{h^*}(\Delta_i^*)\left(\tilde{Y}_i - \theta' V_i\right)^2. \qquad \text{(Eq. 3)}$$

   Here, K denotes the triangular kernel function. The kernel function is defined as $K_{h^*}(\delta) = \frac{K(\delta/h^*)}{h^*}$ giving more weights to the observations closer to the border. The vector $V_i = (1, D_i, \Delta^*, D_i\Delta^*)^\top$ consists of the appropriate transformations of the normalized distance to the border. Additionally, $e_2 = (0,1,0,0)^\top$ is the unit vector that selects the coefficient of D_i, which is the target parameter. We derive robust confidence interval for each specification for every time period considered following Cattaneo, Idrobo, and Titiunik 2024

5. *ML Based Geographic Diff-in-Disc Estimator.* Finally, we iterate the previous steps over each time period, defining τ_{baseline} as the discontinuity in price at the time when mandatory disclosure was introduced. For each subsequent and prior time periods, we compute the pairwise difference relative to τ_{baseline}, which provides us with the Average Treatment Effect and allows for the examination of the dynamics in the pre-treatment periods (placebos).

$$\tau^{RDDisc}_{\text{With Adjust}}(t) = \tau_t - \tau_{\text{baseline}}, \quad t \neq \text{baseline}, \qquad \text{(Eq. 4)}$$

where τ_t represents the treatment effect for period t, and τ_{baseline} is the treatment effect for the baseline period. These pairwise differences are used to assess both the ATE and the validity of the placebo tests, ensuring that no significant treatment effects are observed prior to the introduction of mandatory disclosure.

a. We report the average R^2 values over these 5 folds in tables 5, 6, 8, and 7 for each of the models and time period considered

b. We select the nuisance function η_0 which minimizes the residual mean squared error (RMSE) for each time period t.

3.1.2 Results

Non-linear methods consistently used in the first stage adjustment outperform alternative approaches, providing the most accurate fit for predicting listed prices, particularly when high-dimensional covariates are considered. This is clearly reflected in the coefficient of determination tables[20], which present various specifications of the nuisance function η_0 across different samples, underscoring the complexity inherent in capturing spatial effects. Notably, the linear model consistently underperforms over time and across all sample groups as it systematically overfit the data in our high dimensional setting. In the smallest sample, we observe statistically significant results only when covariates are adjusted using non-linear methods. Without such adjustments, the raw results fail to reveal any significant discontinuous change in prices for energy-efficient properties listed on the platforms. This finding reinforces the importance of applying appropriate estimation techniques to uncover meaningful price dynamics, particularly in our smaller sample. These results not only validate the effectiveness of our overall estimation strategy but also illustrate the nuanced application of non-linear adjustments in enhancing the accuracy and reliability of the estimates.

We present the adjusted and non-adjusted aggregated results in Tables 9 and 10 respectively. Table 9 showcases the time-series estimates of $\tau^{RDDisc}_{With\ Adjust}$ for the full sample. These estimates were derived using our General Estimation Procedure described earlier and are robust to both longitudinal and latitudinal spatial effects, as well as property-specific characteristics. In Table 9, we identify the method that yielded the highest accuracy, as measured by the R^2 statistic, for each time period. This is derived from fitting the nuisance function $\hat{\eta_0}$ using a range of non-linear specifications. Table 10, in contrast, reports the results of $\tau^{RDDisc}_{Without\ Adjust}$, derived without any adjustments applied (i.e., directly on $Y_i(h,t)$ rather than $Y_i(h^*,t) - \hat{\eta_0}_s(h^*, Z_i, t)$). The adjusted τ estimates consistently exhibit lower standard errors across all time periods, yet no significant differences are found when compared to the unadjusted estimates.

The adjusted estimates demonstrate greater stability over time and suggest that mandatory disclosure did not have a statistically significant effect on housing prices at the aggregate level. Despite this, a closer examination of the heterogeneous effects of the policy reveals that it had a significant negative impact on the asking prices of listed properties with poor EPC scores (i.e the energy intensive properties). Specifically, the asking price decreased by an average of -10.8 percentage points one year after the enforcement of the policy and -11.9 percentage points two years after its implementation. The pre-treatment estimates indicate that the asking prices for energy-intensive properties in France did not differ significantly from those in Belgium over the years, supporting the parallel trends assumption, as shown in Table 11. Furthermore, properties classified as energy-balanced or energy-efficient neither benefited from nor were penalized by the policy. We find no statistically significant change in the asking prices for these property types post-treatment, as detailed in Tables 13 and 16 respectively.

These results suggest that the policy was effective in penalizing energy-intensive properties, achieving the intended impact of lowering their prices. However, when examining other property types, such as energy-efficient and energy-balanced dwellings, the policy shows no clear evidence of impact. The adjusted and unadjusted estimates for energy-efficient properties are presented in Figures 15 and 16, respectively, while the corresponding results for energy-balanced properties appear in Figures 13 and 14. These properties did not experience any statistically

20. Tables 5, 8, 7, and 6 present the results of the first-stage predictions of the R^2 values, where the log-transformed square meter listed price is regressed on our high-dimensional set of covariates, both to the left and right of the cutoff. These predictions are derived for four distinct sample groups: the full sample (table 5), the energy-efficient sample (table 8), the energy-balanced sample (table 7), and the energy-intensive sample (table 6). For each of these groups, we report a range of specifications for the nuisance function η_0 over multiple time period. Both linear and non-linear specifications of the nuisance function η_0 are considered in order to capture different potential patterns of behavior within the samples.

significant changes in asking prices, indicating that the policy did not provide substantial incentives or penalties for these categories. This suggests that the policy's effect was largely concentrated on properties with poor energy performance, rather than creating a broad and balanced pricing gradient that would encourage energy-efficient property investments or disincentivize energy-intensive properties across the board.

Our findings show that the policy successfully reduced asking prices for properties with poor EPC scores, motivating owners to renovate. At the same time, it did not lead to significant price increases for energy-efficient properties, allowing these properties to stay within reach for a wider range of buyers. By stabilizing prices for energy-efficient dwellings and encouraging renovations in inefficient properties, the policy strikes a balance between incentivizing energy improvements and protecting access to affordable housing, thus mitigating any risk of eviction form energy efficient housing (at least locally).

3.2 Estimating the heterogeneous effect of mandatory disclosure on housing price nationwide

In this section, we aim to extend the results of the previous analysis to the entire territory. It is quite plausible that the effect estimated at the border differs across other local environments. For example, the south of France experiences considerably more sunny days than the north[21]. These geographic and climatic contrasts may influence how prospective buyers value energy efficiency: households in sunnier southern areas, being less exposed to energy shocks and likely consuming less energy for heating, may place less emphasis on energy performance when purchasing property; therefore, we expect that the estimated effect computed at the border will be less pronounced on energy intensive properties.

As noted in the introduction, the primary challenge in this analysis stems from the nature of the regulation itself. Implemented at the national level and applying to all property listings posted since July 2021, the policy does not naturally provide a clear treatment and control group, making it difficult to identify causal effects in the traditional difference-in-differences sense. To address this, we focused on properties located along the national border, reasoning that cross-border markets combined to staggered adoption may offer quasi-experimental variation. The results from this border study support a critical working assumption: properties with balanced energy performance ("energy-balanced" properties) appear to have been unaffected by the regulation. This assumption is intuitively plausible. Homes with mid-range energy ratings are generally perceived by buyers and sellers as representative of the average property, so the introduction of the regulation is unlikely to have altered their pricing mechanism significantly. In other words, these properties should function as a stable benchmark: because the market already treats them as "standard," their prices provide a reference point largely insulated from the policy shock. Extending this insight, energy-balanced properties can therefore serve as a quasi-control group in broader territorial analyses. By comparing changes in prices of lower- or higher-efficiency homes against this stable mid-efficiency segment, we can better isolate the regulation's impact on valuation patterns across different regions and climates north versus south, apartment versus houses, and so forth. Most importantly, we observe listings published without an EPC score (non-compliant sellers/realtors). This will allow us to understand how the market values non-disclosure under this regulation, by comparing their pricing and market performance to that of homes with mid-range EPC ratings.

3.2.1 Generalization. Two steps estimation procedure

The objective of our study is to estimate the effect of mandatory energy performance disclosure on the dynamics of green premia across the country. Specifically, we aim to compare energy-balanced properties (which will serve as our control group) with energy-inefficient properties, energy-efficient properties, and non-compliant listings (those listed without an EPC score). Our study will employ a two-step estimation strategy.

The first step of our estimation strategy focuses on consistently estimating the dynamics of green premia over time and across different regions. We anticipate that preferences for energy performance will vary significantly across different locations, which could impact local pricing mechanisms. In an ideal scenario, we would observe the exact same property listed with different EPC scores in each local market in France, and with the same other features, sold over different time periods, both before and after the regulation is implemented. Under these conditions,

21. According to Hello Watt, northern departments bordering Belgium such as Nord, Pas-de-Calais, and Aisne receive an average of about 125, 130, and 142 sunny days per year, respectively. In contrast, departments with a Mediterranean climate like Bouches-du-Rhône, Var, and Alpes-Maritimes enjoy nearly twice as many, with approximately 235, 245, and 253 sunny days annually.

we could directly compare the price of these properties over time to identify the causal effect of the regulation, assuming that properties with an energy-balanced EPC score remain unaffected by the new regulations. However, since we do not have access to such ideal data, we will rely on an econometric strategy to approximate this situation. First, because our data consists of repeated cross-sectional samples, it is essential that each subsequent dataset we analyze is comparable to previous ones. This ensures that any shifts in the composition of properties over time are accounted for, maintaining the consistency of our analysis. Second, recognizing that preferences for energy performance are likely to be spatially heterogeneous, we will identify a set of reasonable local housing markets where we can estimate the dynamics of green premia for each property type. Finally, because we observe a wide range of property features in the listings, we will control for these in a hedonic model. By fixing the same reference property across the four property types in each market and over every time period, we can control for compositional changes and ensure comparability between local markets. This will allow us to make meaningful comparisons between property types over time and across locations.

Once the hedonic price indices are calculated for each local market and energy-consumption type, we will estimate the average treatment effect of mandatory energy performance disclosure over time in an event-study framework, controlling for both local market and time fixed effects. This will allow us to compare the price indices of energy-balanced properties with those of energy-inefficient properties, energy-efficient properties, and non-compliant listings.

Estimation Procedure. *Two Step Strategy*

1. *Building EPC specific clustered hedonic price indices*

   We adopt the clustering approach defined by INSEE[a]. This approach identifies city centers and the neighboring municipalities within their influence, creating a distinct housing market. The clustering reflects typical commuting times and local labor market conditions. We then filter our listing database according to these clusters and segment the market into apartments and houses. Additionally, we further segment the dataset based on their respective EPC scores (when available), categorizing the properties into four types: energy-balance properties (scores C, D, E), energy-intensive properties (scores F and G), energy-efficient properties (scores A and B), and non-compliant properties (those without an EPC score). We then estimate the following hedonic regression model fixing the same reference property for each of these sub-markets collecting the constant and the time dummy coefficient in this regression model to build our EPC specific price indices per markets:

$$I(\text{EPC}, g, t) : \begin{cases} \ln(p_i)|_{(\text{EPC},g)} & = \gamma_0 + \sum_{k=1}^{K} \beta_k X_{ik} + \gamma_t \cdot T_i + \epsilon_i \\ I(\text{EPC}, g, t \neq 0) & = 100 \times \exp(\gamma_t) \\ I(\text{EPC}, g, t = 0) & = 100 \end{cases} \quad \text{(Eq. 5)}$$

   - g local housing market (INSEE cluster)
   - t period
   - EPC group
   - X_i vector of property features (rooms, bedrooms, floor, distance to city center...) of listing i
   - p_i squared meter price of listing i

2. *Event-Study Design*

   This panel data is then used to assess the impact of mandatory energy performance disclosure on square meter prices, comparing the price dynamics of energy-balanced properties to the other three groups, both before and after the enforcement of mandatory disclosure in July 2021.

$$I_{gt} = \sum_{j \in \{-m, \cdots, 0, \cdots, n\}}^{n} \gamma_j \cdot D_{g,t-j} + \alpha_g + \delta_t + \beta \cdot X_{gt} + \epsilon_{gt} \quad \text{(Eq. 6)}$$

- g local market (EPC group x INSEE cluster)
- t time period
- X_{gt} volume of listings in a specific local market (EPC group x INSEE cluster)
- I_{gt} price index for a given local market (EPC group x INSEE cluster)
- δ_t time fixed effect
- α_g local market fixed effect
- γ_j captures the ATE at time j of the EPC group treated compared to the control (energy balanced properties)

a. The "Functional Areas of Cities 2020" zoning by INSEE defines clusters of municipalities based on commuting patterns and urban functions, categorizing them into levels (A to D) based on population size and employment. This classification includes both French and cross-border regions, with each cluster representing a unified economic and social area centered around a city. For more details on the methodology and descriptions, refer to INSEE's official document: insee.fr

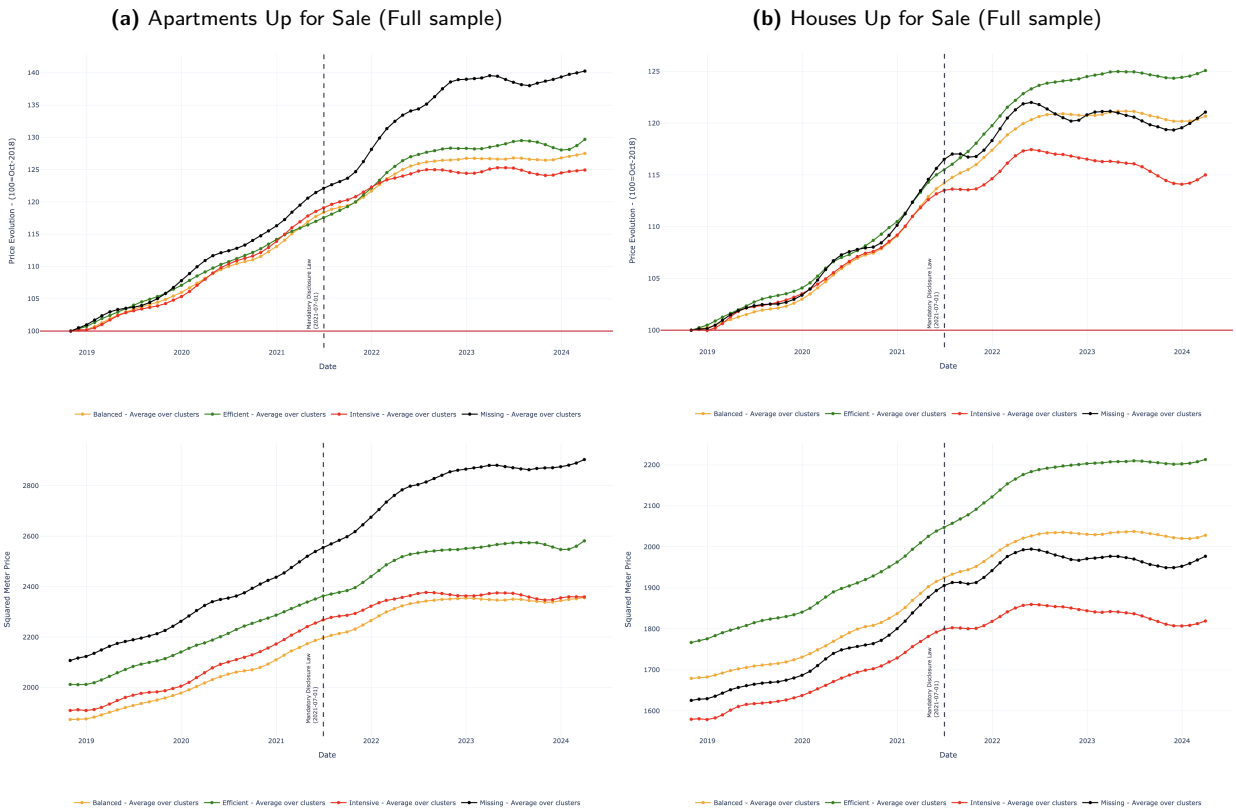
3.2.2 Results

Following the estimation procedure outlined previously, we compiled our panel and estimated multiple hedonic models for houses and apartments listed for sale on the SeLoger website between 2018 and 2024. In Figure 15, we present the distribution of the adjusted R-squared values across markets, categorized by energy consumption groups. Our results indicate robust predictive power across the entire sample, regardless of the local market or property type (apartments or houses). Specifically, the average adjusted R-squared values range from 44% to 48% for apartments and from 35% to 43% for houses.

Figure 10 and Table 17 reveal the presence of a *green premium*, notably, a consistent price advantage for energy-efficient dwellings (*Balanced* and *Efficient* categories) that appears to persist across the sample period and is visible across different points of the price distribution (means, medians, 25th and 50th percentiles). Importantly, this premium is already observable before the 2021 policy intervention mandating energy performance disclosure, suggesting that market participants had already capitalized energy efficiency into housing prices even in the pre-treatment period. However, differences emerge between the two market segments. For houses, the brown discount (penalization of energy-intensive dwellings) is clearly visible before 2021 and appears to deepen after mandatory disclosure, suggesting stronger market sensitivity to energy inefficiency. In contrast, the apartment market exhibits a less pronounced brown discount, energy-intensive apartments are often priced similarly to balanced ones, and more surprisingly the missing EPC category is systematically priced above the efficient segment. This asymmetry suggests that informational frictions and perceived energy cost salience differ across housing types, with house buyers responding more strongly to EPC labels than apartment buyers. Overall, the descriptive evidence supports the existence of persistent green premia and evolving brown discounts, consistent with the subsequent panel estimates reported in figures 17 to 19.

Following the estimation procedure outlined above, Figure 11 presents the event study estimates by energy consumption category. Specifically, the figure compares each group of dwellings, classified by their level of energy consumption, to the benchmark group of energy-balanced properties, thereby quantifying the causal effect of mandatory energy performance disclosure. A first salient finding emerging from Figure 11 concerns the placebo estimates associated with the pre-treatment periods. These estimates provide empirical support for the validity of the parallel trends assumption across different markets and indices. The only exception pertains to houses offered for sale not disclosing their EPC rating, for which the results are too imprecise to allow for credible inference. More specifically, the evidence suggests that, prior to the policy intervention, the price dynamics of energy-balanced dwellings (the reference category) closely mirrored those of both energy-intensive and energy-efficient properties, as well as apartments not reporting their energy performance.

Figure 10. Unweighted Average apartment and house prices and price indices per EPC group



Note. The figure reports unweighted averages of predicted apartment and house prices, as well as corresponding price indices, across INSEE clusters by EPC category. These series are constructed from the cluster-level hedonic estimates obtained in the first step of our procedure. For each EPC group, the colored lines trace the evolution of average predicted prices over time, while price indices are normalized to 100 in October 2018. The vertical dashed line marks the introduction of mandatory EPC disclosure.

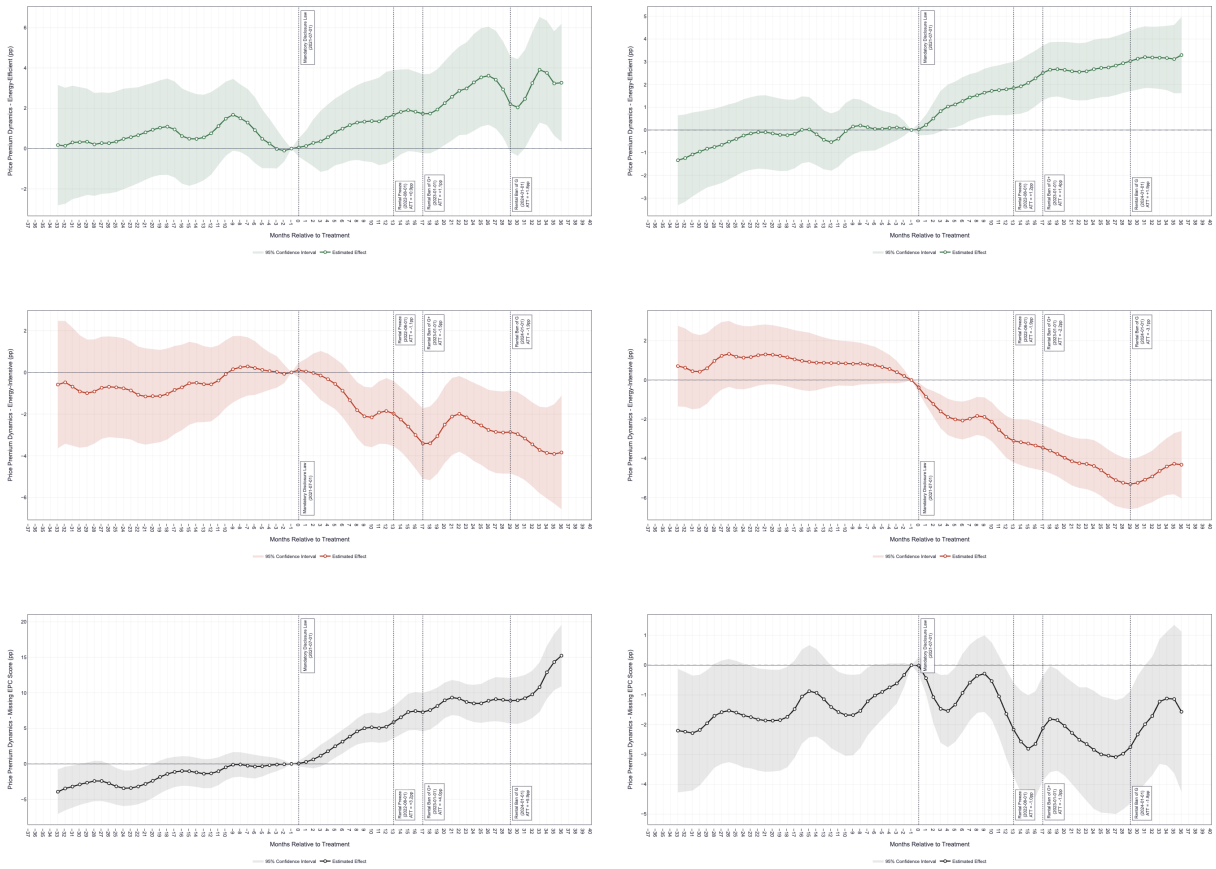
In the market for apartments, the estimated effects display notable heterogeneity across energy performance categories. For energy-efficient apartments offered for sale, the estimated treatment effect is relatively small and positive, though not statistically significant. Specifically, the average treatment effect on the treated (ATT) is approximately +1 percentage point one year after the implementation of mandatory disclosure, relative to energy-balanced apartments. This finding indicates that the introduction of mandatory disclosure did not generate an "eviction effect" that would have rendered energy-efficient properties systematically more expensive. Instead, price differentials appear to have remained largely unaffected by the policy in this segment.

In contrast, the results for energy-intensive apartments reveal a modest but statistically significant negative effect as reported by Figure 11. The ATT is approximately –1.1 percentage points one year after the introduction of mandatory disclosure, increasing in magnitude to about –2 percentage points after twenty-nine months. This pattern suggests that mandatory energy performance disclosure induced a meaningful price discount for energy-intensive dwellings, a discount attributable primarily to their poor energy performance rather than to other confounding factors.

More strikingly, the analysis uncovers a substantial and statistically significant positive effect for apartments not disclosing their EPC score. For this group, the ATT is approximately +3.2 percentage points one year after the policy's implementation. This result runs counter to the theoretical predictions of information disclosure models, particularly those of Grossman 1981 and Milgrom 1981, which posit that non-disclosure should be interpreted by the market as an indicator of the lowest possible energy performance rating, leading to a price discount similar to that observed for energy-intensive properties. Contrary to these theoretical expectations, the observed premium for non-disclosing properties suggests that the market response may have been driven by alternative mechanisms, such as market tension, perceived quality differences but also heterogeneous preferences over energy performance.

Figure 11. Dynamic effect of mandatory energy performance disclosure on the listing price of apartments and houses up for sale across various energy consumption levels

(a) Apartments Up for Sale (Full sample) **(b)** Houses Up for Sale (Full sample)



Note. The panels present event-study estimates from the second step of our two-step hedonic procedure. Each series plots the monthly change in hedonic listing prices of the reference property around the introduction of mandatory EPC disclosure, separately by energy-consumption group and property type. Shaded bands represent 95% confidence intervals. These dynamics trace how the policy's effect on predicted apartment and house prices evolves before and after the disclosure requirement in July 2021.

In the housing market, the estimated effects align more closely with both theoretical expectations and prior assumptions. Before the policy intervention, the price trajectories of energy-balanced dwellings (the reference category) closely tracked those of both energy-intensive and energy-efficient properties. The pre-treatment estimates for these two groups are statistically insignificant and remain approximately parallel to the x-axis, indicating no pre-existing trends that would bias the estimation. In contrast, the estimates for dwellings with unreported energy performance deviate from this pattern, preventing us from drawing any reliable inference for that subgroup.

Following the policy's introduction, the estimated treatment effect for energy-efficient dwellings is positive, statistically significant, and appears to persist over time. Specifically, the average treatment effect on the treated is around $+1.2$ percentage points over one year after the policy implementation, increasing to approximately $+2$ percentage points over the 29 months afterward. This sustained rise suggests that the regulation may have generated an "eviction effect", whereby higher property prices for energy-efficient dwellings reduced their affordability and accessibility to potential buyers. Conversely, for energy-intensive dwellings, we find a negative and statistically significant impact: prices decreased by roughly 2 percentage points within one year of the policy's implementation and by around 3.1 percentage points over the subsequent 29 months. This decline is consistent with the interpretation that the regulation penalized less energy-efficient housing, potentially reflecting lower demand or increased market discounting for properties with poor energy performance.

3.2.3 Anticipatory Effects

Our estimates may be subject to contamination and anticipatory behavior arising from the sequential implementation of multiple policy components following the introduction of the mandatory disclosure of energy performance scores. In particular, when market participants anticipate subsequent regulatory interventions, their expectations may be capitalized into current prices. Prospective buyers, foreseeing tighter energy-related restrictions or incentives, may adjust their willingness to pay accordingly, while sellers may revise their asking prices in anticipation of future shifts in market demand. Consequently, our estimated effects may not exclusively capture the impact of the mandatory disclosure itself but also reflect forward-looking adjustments in pricing behavior induced by expectations of additional measures.

This concern is particularly relevant given the multi-stage design of the legislation, which includes several treatments potentially influencing our outcome of interest, namely, housing asking prices. Following the initial disclosure requirement, the law introduced a rental price freeze for the most energy-inefficient dwellings (effective 13 months later, in August 2022) and, more substantially, a rental ban on properties rated G, set to take effect 31 months after the initial disclosure mandate (January 2025). A limited earlier restriction also applied to "G+" dwellings, removed from the rental market in January 2023, though this represents a very small segment of both the rental and sales stock and is thus unlikely to have materially affected transaction prices.[22]

The staggered timing of these policy components complicates long-term identification, as price adjustments may embed expectations of these later interventions. Such contamination limits our ability to isolate and interpret the persistence of treatment effects beyond the short term. However, we contend that, prior to the introduction of the rental freeze in August 2022, our estimates are likely to cleanly identify the direct impact of mandatory disclosure on prices. This argument rests on several points.

First, the subsequent regulations primarily target the rental market, whereas our analysis concerns the sales segment, which is less directly exposed to immediate restrictions such as the rental freeze or the rental ban on low-rated dwellings. Accordingly, anticipatory behavior in the sales market should be limited in the short run. Second, the political context of 2024 introduced substantial uncertainty regarding the enforcement of later provisions. The dissolution of the National Assembly in June 2024 and the broader political instability during that period undermined confidence in the timely implementation of the rental ban. Contemporary press articles[23] and policy commentaries (see Figures 22) suggest that the enforcement of the January 2025 rental ban on G-rated dwellings was increasingly uncertain, likely weakening any forward-looking price responses in anticipation of that regulation.

Taken together, these considerations suggest that while our longer-term estimates may partially capture anticipatory effects as well as other related to the broader policy package, the short-term estimates preceding July 2021 can be interpreted with greater confidence as reflecting the pure effect of the mandatory disclosure of energy performance on housing prices.

4 Conclusion

The study investigates whether the canonical prediction of full information holds in a real housing market subject to mandatory energy performance disclosure. Using rich listing data from France and Belgium and exploiting the 2021 French reform as a natural experiment, the analysis reveals a complex market response. While the regulation strengthened the salience of energy performance and generated expected price adjustments for highly efficient and highly inefficient dwellings, it also produced a striking (and theoretically unexpected) premium for nondisclosed EPC ratings, most notably in the apartment market several years after implementation. This pattern stands in direct tension with the classic unraveling mechanism and invites a deeper reflection on the frictions that prevent full transparency from emerging in practice.

22. The "G+" category accounts for only a marginal share of the housing market, primarily affecting units already within the rental segment, and therefore should not bias our sales price estimates.

23. *"DPE : interdire à la location les logements E, F, G divise les députés"*, La Tribune, 22/10/24
"Interdiction à la location des passoires thermiques : Bruno Le Maire prêt à revoir le calendrier", Les Echos, 27/11/2023
"Immobilier : les pistes pour desserrer les contraintes sur les passoires thermiques", Les Echos, 08/10/24
"Immobilier : l'interdiction de louer des passoires thermiques à partir du 1er janvier 2025 peut-elle être suspendue ?", Les Echos, 23/10/24

Several mechanisms may help explain why non-disclosure persists and is even rewarded in certain segments. A first explanation relates to heterogeneous preferences for energy performance across space and buyer types. In markets where energy efficiency is less valued, whether due to milder climates, differing household budgets, or alternative priorities, buyers may discount the informational value of EPC ratings. In such contexts, the absence of disclosure need not be interpreted as evidence of the worst possible rating; instead, it may be perceived as largely irrelevant or even as a signal that other property attributes justify the asking price. This heterogeneity naturally weakens the informational dominance of EPC labels and undermines the universal logic of unraveling.

A second mechanism concerns partial or asymmetric information among the sellers themselves. Many property owners may possess only limited understanding of their dwelling's true energy performance, especially when EPCs are outdated, recently revised, or based on complex technical criteria. Sellers who are uncertain about their score may rationally avoid disclosure if they suspect their property could perform poorly but are unwilling to invest time or financial resources to confirm it. This form of "rational ignorance" effectively disrupts the sequential disclosure cascade predicted by theory: if some sellers do not possess accurate information, they cannot strategically disclose, and buyers cannot interpret non-disclosure as a deliberate concealment.

A third potential explanation lies in market segmentation and attribute bundling. Apartments, in particular, often trade on amenities, location, proximity to transport, and neighborhood prestige, which may dominate energy considerations in buyers' utility. When EPC information becomes mandatory, some sellers may respond by emphasizing other salient attributes, and buyers, in turn, may infer that missing EPC data simply reflects a listing strategy rather than underlying poor quality. In such environments, the EPC becomes only one of many noisy signals, and its absence may have ambiguous or even positive valuation effects.

Fourth, mandatory transparency itself may generate unintended behavioral responses and reputational spillovers. If some sellers comply while others do not, the visibility of compliance could create a form of "signal fatigue," where buyers observe so much variation in reporting behavior that the absence of an EPC loses its informational content. In such a setting, nondisclosure may be interpreted as a benign oversight rather than a strategic attempt to hide a poor score. Similarly, buyers may perceive disclosed poor ratings as more credible than disclosed good ones, reducing the informativeness of disclosure and altering strategic incentives.

Taken together, these mechanisms suggest that the unraveling theorem, while elegant in theory, rests on behavioral, informational, and institutional assumptions that real housing markets rarely satisfy. The evidence presented in this study underscores the need to consider a broader set of frictions shaping disclosure behavior, particularly when regulations attempt to correct information asymmetries.

5 Annexes

5.1 Robustness checks - ML Based Geographic Difference in Discontinuity

Traditional RDD Assumptions. *Between 2015 and 2021 France is not under stringent mandatory disclosure while it is the case for Belgium which create a discontinuity in price at multiple EPC levels.*

Continuity. Assumes that, in the in the absence of the policy change at the boundary, the potential outcomes (e.g., housing prices) would vary smoothly with distance and would not jump exactly at the border. In practice, this means properties just inside France and just inside Belgium are comparable on unobservables, so any discontinuity is attributed to the policy contrast.

Local Randomization. Treats observations sufficiently close to the border as if they were randomly assigned to the French or Belgian side. Within a narrow bandwidth, the two groups should look similar in pre-treatment characteristics.

No Manipulation Around the Cutoff. Assumes individuals or agents cannot precisely sort to one side to gain policy advantages (e.g., list or transact a property just across the line). If strategic sorting were possible, discontinuities could reflect selection rather than treatment effects.

Homogeneity of Treatment Effect (Locally). Assumes the treatment effect is approximately constant for units infinitesimally close to the same side of the border. Large differences in amenities, zoning, school quality, or historical legacies that change sharply at the boundary can induce effect heterogeneity and complicate interpretation.

Smoothness of Covariates. Requires that predetermined characteristics (demographics, accessibility, local economic indicators) evolve smoothly at the cutoff. Sharp cross-border jumps in these covariates would threaten identification.

Consistency and Precision of the Running Variable. The running variable, often geodesic distance to the border must be measured accurately so that each observation is correctly classified as France vs. Belgium and placed at the right distance. Misclassification (e.g. addresses miss-reporting, undisclosed addresses...) attenuates estimated effects and can bias bandwidth selection.

5.2 Random Sampling of Fuzzy Location

In our study, one of the challenges we face is dealing with missing or inaccurately reported geographical data (street names, zip codes, street numbers...) specifically regarding longitudes and latitudes in property listings on SeLoger. In some cases, the location information for properties may be either absent or imprecisely reported. Rather than excluding these observations from our analysis, we have devised an alternative solution to retain valuable data without compromising the integrity of our results. We validate and enrich the reported property information by leveraging Elastic Search, a powerful search and analytics engine designed to quickly retrieve and analyze large volumes of structured and unstructured data. In this process, Elastic Search allows us to precisely identify the geographical location of each property by cross-referencing addresses, coordinates, and other location-related attributes. This step ensures that our dataset is accurate and that subsequent analyses are based on correctly geolocated properties, reducing errors that could arise from inconsistent or incomplete reporting.

When longitude and latitude values are incorrectly reported or missing, dropping these observations could lead to a significant reduction in the dataset size. This, in turn, could bias the results or lead to a less representative analysis of the overall property market. Therefore, we seek a way to handle such cases without losing important data. To address this issue, we introduce a method called Random Sampling of Fuzzy Location. The idea behind this approach is to generate plausible coordinates for the properties whose exact locations are unknown, but whose corresponding city is known. This step allows us to compute *"fuzzy distances"* for any points lying in the selected geographic buffer around the border.

The term *"fuzzy location"* refers to cases where the precise coordinates (longitude and latitude) of a property are unavailable, but we still have information indicating that the property lies within a specific, known area, such as a city or neighborhood. This geographical context is often included in the available data. Instead of making assumptions about the property's location such as placing it at the city's centroid or discarding the data point altogether, we treat the location as uncertain but still confined within the boundaries of the known area.

Figure 12. Random Sampling of Fuzzy Location



France - $\bar{\Delta}^{c}_{\{i,t\}} = 20$km

Belgium - $\bar{\Delta}^{c}_{\{i,t\}} = 20$km

Note. The maps illustrate the randomization procedure applied to listings with fuzzy geographic locations. For each observation, a coordinate is randomly drawn within its reported city geometry (here shown for a two municipalities located at 20km from the border) and used as the working location in the analysis. Points marked "Random" represent these simulated coordinates, while "Not Random" denotes listings with precisely reported coordinates. The panels display examples for France (left) and Belgium (right).

To address this, when the precise location is unknown we randomly select a point within the defined boundary of the city to represent the property's location (see Figure 12). This selection is probabilistic, ensuring that the generated coordinates are realistic and fall within the area's known geographic limits. The benefit of this approach is that it prevents the creation of mass-points in our dataset. For example, if every property within a city were assigned to its centroid, this would artificially group all listings at the same location, leading to distorted analyses. This mass-point effect would not only introduce bias into the data but also affect procedures such as bandwidth selection, potentially excluding numerous observations and reducing the accuracy of the results. By selecting a plausible location within the city, we maintain the integrity of the data while still respecting the uncertainty inherent in the lack of exact coordinates.

The main objective of this method is to generate a plausible location for properties where the exact coordinates are missing but where the city or region is known. This allows us to retain these observations in our analysis without making overly simplistic assumptions or introducing significant bias. By generating realistic coordinates within the given area, we can maintain the robustness and representativeness of the dataset, thus improving the overall quality of our analysis and ensuring the highest geographical accuracy.

5.3 Covariates balance and descriptive statistics

Table 1. Descriptive statistics - Houses listed for sale on SeLoger between 2018 and 2024 (France, whole sample)

	Balanced			**Efficient**			**Intensive**			**Missing**		
Covariates	**Post**	**Pre**	**Delta**	**Post**	**Pre**	**Delta**	**Post**	**Pre**	**Delta**	**Post**	**Pre**	**Delta**
Bathroom count												
- #0	13.9%	11.7%	2.2 pp	12.2%	10.4%	1.8 pp	17.0%	14.7%	2.3 pp	19.1%	18.3%	0.8 pp
- #1	52.9%	56.9%	-4.0 pp	55.4%	58.3%	-2.9 pp	47.6%	52.4%	-4.8 pp	43.4%	47.9%	-4.5 pp
- #2	7.1%	9.3%	-2.2 pp	7.6%	10.3%	-2.7 pp	5.0%	5.8%	-0.8 pp	5.8%	6.5%	-0.7 pp
- #3+	0.7%	0.9%	-0.2 pp	0.8%	1.3%	-0.5 pp	0.5%	0.5%	0.0 pp	0.8%	0.8%	0.0 pp
- #NA	25.5%	21.1%	4.4 pp	23.9%	19.8%	4.1 pp	30.0%	26.5%	3.5 pp	31.0%	26.5%	4.5 pp
Vintage year												
- $\leq$ 1799	0.8%	1.0%	-0.2 pp	0.6%	0.9%	-0.3 pp	0.9%	1.0%	-0.1 pp	1.0%	1.2%	-0.2 pp
- 1800 - 1914	10.4%	8.9%	1.5 pp	6.7%	7.4%	-0.7 pp	14.0%	9.4%	4.6 pp	12.3%	13.1%	-0.8 pp
- 1915 - 1945	6.1%	4.4%	1.7 pp	3.3%	3.3%	0.0 pp	8.6%	4.5%	4.1 pp	5.3%	5.4%	-0.1 pp
- 1946 - 1974	18.1%	15.0%	3.1 pp	8.1%	5.9%	2.2 pp	25.2%	25.7%	-0.5 pp	9.1%	7.9%	1.2 pp
- 1975 - 1990	16.0%	16.1%	-0.1 pp	10.0%	9.3%	0.7 pp	5.7%	10.7%	-5.0 pp	5.4%	5.0%	0.4 pp
- 1991 - 2003	5.6%	6.3%	-0.7 pp	9.4%	11.5%	-2.1 pp	0.4%	1.1%	-0.7 pp	2.4%	2.5%	-0.1 pp
- $\geq$ 2004	5.5%	7.7%	-2.2 pp	31.1%	25.9%	5.2 pp	0.2%	0.7%	-0.5 pp	9.1%	6.9%	2.2 pp
- NA	37.4%	40.5%	-3.1 pp	30.8%	35.7%	-4.9 pp	44.9%	46.9%	-2.0 pp	55.3%	57.9%	-2.6 pp
Electricity as primary energy source												
True	28.3%	28.4%	-0.1 pp	23.6%	17.7%	5.9 pp	23.4%	33.2%	-9.8 pp	19.3%	21.3%	-2.0 pp
Room count												
- #1	0.0%	0.0%	0.0 pp	0.0%	0.0%	0.0 pp	0.1%	0.1%	+0.0 pp	0.3%	0.2%	0.1 pp
- #2	1.2%	0.9%	0.3 pp	0.5%	0.4%	0.1 pp	3.1%	3.3%	-0.2 pp	4.1%	3.1%	1.0 pp
- #3	9.4%	8.2%	1.2 pp	6.0%	5.0%	1.0 pp	17.5%	18.3%	-0.8 pp	14.8%	14.3%	0.5 pp
- #4	24.4%	23.6%	0.8 pp	25.6%	22.9%	2.7 pp	28.0%	29.4%	-1.4 pp	27.9%	26.7%	1.2 pp
- #5+	65.0%	67.3%	-2.3 pp	67.9%	71.6%	-3.7 pp	51.3%	49.0%	2.3 pp	52.8%	55.7%	-2.9 pp
Cellar												
True	22.0%	21.2%	0.8 pp	13.1%	15.4%	-2.3 pp	28.7%	25.3%	3.4 pp	20.3%	21.9%	-1.6 pp
Average living area (m^2)	119.86	122.76	-2.36%	128.68	135.37	-4.94%	104.61	101.25	3.32%	112.73	114.86	-1.86%
Average price per square meter (€/m^2)	2 217	1 914	15.8%	2 542	2 140	18.8%	1 885	1 718	9.7%	1 868	1 610	16%
Average distance to the city center (km)	19.64	20.04	-0.02%	17.80	16.89	0.05%	20.02	22.28	-0.10%	17.75	17.75	0.00%
Count of listed properties	1 252 745	1 176 896	6.4%	620 597	487 940	27.2%	318 724	186 386	61.0%	455 279	641 294	-33.2%
Relative share	47.3%	47.2%	0.1 pp	23.4%	19.6%	3.8 pp	12.0%	7.5%	4,5 pp	17.2%	25.7%	-8.5 pp

Note: Descriptive statistics for houses listed for sale on SeLoger in France from 2018 to 2024. The policy intervention is the introduction of mandatory energy performance certificate disclosure in advertisements in July 2021. Columns report post- and pre-intervention values and their differences. Percentages are reported for categorical variables (differences in percentage points), while continuous variables are reported in levels (differences in percent).

Table 2. Descriptive statistics - Apartments listed for sale on SeLoger between 2018 and 2024 (France, whole sample)

	Balanced			Efficient			Intensive			Missing		
Covariates	Post	Pre	Delta	Post	Pre	Delta	Post	Pre	Delta	Post	Pre	Delta
Bathroom count												
- #0	16.2%	15.1%	1.1 pp	16.6%	14.0%	2.6 pp	18.4%	18.2%	0.2 pp	41.3%	26.0%	15.3 pp
- #1	49.5%	58.3%	-8.8 pp	52.9%	57.5%	-4.6 pp	37.9%	50.2%	-12.3 pp	33.2%	44.0%	-10.8 pp
- #2	1.2%	1.5%	-0.3 pp	1.8%	2.1%	-0.3 pp	0.7%	1.1%	-0.4 pp	1.5%	1.3%	0.2 pp
- #3+	0.0%	0.1%	-0.1 pp	0.1%	0.1%	0.0 pp	0.0%	0.0%	0.0 pp	0.0%	0.1%	-0.1 pp
- #NA	33.0%	25.0%	8.0 pp	28.6%	26.2%	2.4 pp	42.9%	30.5%	12.4 pp	23.9%	28.6%	-4.7 pp
Vintage year												
- $\leq$ 1799	0.5%	0.5%	0.0 pp	0.2%	0.4%	-0.2 pp	0.7%	0.7%	0.0 pp	0.2%	0.5%	-0.3 pp
- 1800 - 1914	7.5%	4.3%	3.2 pp	2.8%	3.2%	-0.4 pp	17.2%	8.2%	9.0 pp	3.7%	7.3%	-3.6 pp
- 1915 - 1945	4.5%	2.9%	1.6 pp	1.5%	1.7%	-0.2 pp	10.6%	5.2%	5.4 pp	1.9%	3.8%	-1.9 pp
- 1946 - 1974	24.4%	21.8%	2.6 pp	9.0%	10.9%	-1.9 pp	20.7%	17.6%	3.1 pp	4.8%	10.4%	-5.6 pp
- 1975 - 1990	11.6%	12.2%	-0.6 pp	7.2%	7.7%	-0.5 pp	6.8%	13.3%	-6.5 pp	2.4%	4.8%	-2.4 pp
- 1991 - 2003	5.5%	6.4%	-0.9 pp	6.5%	5.8%	0.7 pp	1.2%	3.6%	-2.4 pp	1.0%	2.1%	-1.1 pp
- $\geq$ 2004	6.7%	8.5%	-1.8 pp	34.7%	26.8%	7.9 pp	0.7%	2.2%	-1.5 pp	8.3%	10.1%	-1.8 pp
- NA	39.3%	43.4%	-4.1 pp	38.2%	43.4%	-5.2 pp	42.1%	49.3%	-7.2 pp	77.7%	61.0%	16.7 pp
Electricity as primary energy source												
True	30.6%	31.9%	-1.3 pp	23.3%	18.7%	4.6 pp	39.8%	46.7%	-6.9 pp	11.1%	22.9%	-11.8 pp
Room count												
- #1	11.4%	9.5%	1.9 pp	5.5%	5.2%	0.3 pp	24.4%	22.7%	1.7 pp	8.9%	12.2%	-3.3 pp
- #2	28.3%	27.3%	1.0 pp	25.2%	21.7%	3.5 pp	39.1%	37.1%	2.0 pp	25.1%	29.8%	-4.7 pp
- #3	34.2%	35.9%	-1.7 pp	40.3%	40.7%	-0.4 pp	24.2%	26.0%	-1.8 pp	33.8%	33.9%	-0.1 pp
- #4	19.2%	20.2%	-1.0 pp	22.3%	24.5%	-2.2 pp	9.2%	10.6%	-1.4 pp	24.7%	18.5%	6.2 pp
- #5+	7.0%	7.2%	-0.2 pp	6.7%	8.0%	-1.3 pp	3.1%	3.5%	-0.4 pp	7.5%	5.7%	1.8 pp
Floor Level												
- Ground floor	18.9%	17.8%	1.1 pp	17.5%	15.7%	1.8 pp	22.5%	24.5%	-2.0 pp	11.5%	16.8%	-5.3 pp
- 1st, 2nd, 3rd	53.7%	53.2%	0.5 pp	55.8%	54.8%	1.0 pp	47.1%	47.8%	-0.7 pp	29.1%	45.5%	-16.4 pp
- 4th, 5th, 6th	15.0%	13.4%	1.6 pp	12.1%	12.8%	-0.7 pp	19.3%	11.4%	7.9 pp	7.9%	12.0%	-4.1 pp
- 7th+	3.8%	3.4%	0.4 pp	2.5%	2.7%	-0.2 pp	3.0%	2.1%	0.9 pp	1.5%	2.6%	-1.1 pp
- NA	8.6%	12.2%	-3.6 pp	12.1%	14.0%	-1.9 pp	8.1%	14.2%	-6.1 pp	50.0%	23.1%	26.9 pp
Elevator												
True	41.4%	41.8%	-0.4 pp	59.8%	57.3%	2.5 pp	24.3%	25.3%	-1.0 pp	57.0%	41.4%	15.6 pp
Cellar												
True	52.4%	51.6%	0.8 pp	29.2%	35.7%	-6.5 pp	51.4%	45.8%	5.6 pp	20.6%	34.7%	-14.1 pp
Average living area (m^2)	60.84	62.19	-2.2%	66.39	68.91	-3.7%	45.69	47.82	-4.5%	64.39	59.88	7.6%
Average price per square meter (€/m^2)	3 928	3 050	28.8%	4 044	3 422	18.2%	4 969	3 307	50.3%	5 156	3 991	29.2%
Average distance to the city center (km)	9.67	11.05	-12.5%	10.06	9.74	3.3%	8.93	12.44	-28%	11.90	9.30	28%
Count of listed properties	1 149 829	945 591	21.5%	606 747	411 959	47.3%	228 944	116 306	96.8%	1 055 236	682 884	54.5%
Relative share	37.8%	43.8%	6 pp	19.9%	19.1%	0.8 pp	7.5%	5.4%	2.1 pp	34.7%	31.7%	3 pp

Note: Descriptive statistics for apartments listed for sale on SeLoger in France from 2018 to 2024. The policy intervention is the introduction of mandatory energy performance certificate disclosure in advertisements in July 2021. Columns report post- and pre-intervention values and their differences. Percentages are reported for categorical variables (differences in percentage points), while continuous variables are reported in levels (differences in percent).

Table 3. Summary statistics – Houses listed for sale at various buffer distances from the France–Belgium border over time

		Area Mean			Bathrooms Median			Build Year Median			Consoenergie Mean			Ln(Price/Area) Mean			Rooms Median			Municipality Count			Obs Count		
Year	**Buffer**	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta
2019	5km	160.43	117.67	-42.76	1	1	0	1 981	1 930	-51	225.04	191.98	-33.05	7.37	7.49	0.12	3	5	2	37	129	92	259	1 597	1 338
		(41.13)	(38.37)		(0.75)	(0.42)		(35.83)	(116.39)		(63.54)	(57.66)		(0.33)	(0.35)		(0.76)	(1.33)							
2019	10km	170.98	120.21	-50.76	1	1	0	1 982	1 958	-24	225.35	202.12	-23.24	7.45	7.58	0.13	3	5	2	41	171	130	304	1 314	1 010
		(37.32)	(37.82)		(0.76)	(0.45)		(28.96)	(183.2)		(63.75)	(57.76)		(0.29)	(0.44)		(0.79)	(1.44)							
2019	20km	169.91	117.97	-51.94	1	1	0	1 983	1 955	-28	222.74	201.59	-21.15	7.45	7.47	0.02	3	5	2	74	282	208	734	3 040	2 306
		(40.93)	(36.7)		(0.73)	(0.44)		(31.3)	(150.41)		(62.38)	(57.96)		(0.28)	(0.36)		(0.77)	(1.5)							
2019	>20km	172.27	128.12	-44.16	1	1	0	1 978	1 970	-8	223.67	212.38	-11.29	7.57	7.32	-0.25	3	5	2	176	1 830	1 654	3 835	13 132	9 297
		(39.84)	(41.36)		(0.84)	(0.47)		(33.32)	(108.84)		(62.32)	(58.93)		(0.3)	(0.34)		(0.83)	(1.54)							
2020	5km	159.6	115.92	-43.68	1	1	0	1 976	1 930	-46	224.82	191.68	-33.14	7.39	7.52	0.14	3	5	2	38	138	100	255	1 473	1 218
		(40.21)	(36.55)		(1.64)	(0.46)		(42.37)	(92.92)		(65.21)	(57.55)		(0.33)	(0.38)		(0.9)	(1.34)							
2020	10km	166.28	118.23	-48.05	1	1	0	1 979	1 956	-23	222.77	194.52	-28.25	7.47	7.63	0.15	3	5	2	43	165	122	265	1 147	882
		(44.69)	(36.52)		(0.88)	(0.45)		(38.87)	(130.62)		(63.29)	(56.97)		(0.3)	(0.44)		(0.88)	(1.54)							
2020	20km	167.12	118.47	-48.65	1	1	0	1 980	1 956	-24	216.96	199.38	-17.58	7.46	7.53	0.06	3	5	2	75	262	187	650	2 378	1 728
		(39.92)	(37.03)		(0.75)	(0.41)		(34.82)	(128.21)		(61.36)	(58.29)		(0.28)	(0.36)		(0.76)	(1.42)							
2020	>20km	172.62	128.09	-44.53	1	1	0	1 977	1 968	-9	219.4	210.89	-8.51	7.6	7.34	-0.26	3	5	2	171	1 796	1 625	3 556	10 641	7 085
		(40.57)	(40.88)		(0.93)	(0.48)		(35.71)	(130.14)		(63.69)	(59.21)		(0.32)	(0.35)		(0.88)	(1.53)							
2021	5km	161.47	112.81	-48.67	1	1	0	1 972	1 930	-42	227.58	197.7	-29.88	7.42	7.59	0.17	3	5	2	34	128	94	279	1 616	1 337
		(42.21)	(34.37)		(0.97)	(0.43)		(36.34)	(61.07)		(61.19)	(58.14)		(0.35)	(0.37)		(0.85)	(1.2)							
2021	10km	167.86	114.77	-53.09	1	1	0	1 970	1 948	-22	223.92	201.38	-22.54	7.48	7.72	0.23	3	5	2	44	178	134	288	1 328	1 040
		(41.8)	(33.89)		(0.74)	(0.45)		(36.9)	(152.27)		(64.15)	(57.23)		(0.32)	(0.46)		(0.84)	(1.33)							
2021	20km	168.37	115.68	-52.69	1	1	0	1 979	1 950	-29	223.27	203.87	-19.4	7.51	7.59	0.08	3	5	2	74	271	197	746	2 624	1 878
		(39.71)	(37.23)		(0.75)	(0.46)		(34.88)	(171.31)		(63.56)	(57.78)		(0.29)	(0.38)		(0.83)	(1.36)							
2021	>20km	169.79	127.25	-42.54	1	1	0	1 974	1 967	-7	219.64	212.11	-7.54	7.64	7.39	-0.25	3	5	2	176	1 914	1 738	3 809	10 666	6 857
		(40.34)	(41.39)		(0.82)	(0.48)		(35.17)	(126.05)		(64.11)	(59.46)		(0.31)	(0.35)		(0.87)	(1.55)							
2022	5km	160.13	111.5	-48.64	1	1	0	1 961	1 930	-31	228.33	203.59	-24.74	7.45	7.63	0.18	3	5	2	35	137	102	314	2 158	1 844
		(41.69)	(34.08)		(0.93)	(0.46)		(38.28)	(34.04)		(60.0)	(57.29)		(0.35)	(0.37)		(0.98)	(1.29)							
2022	10km	172.83	113.17	-59.66	1	1	0	1 974	1 948	-26	227.05	207.94	-19.11	7.53	7.78	0.26	3	5	2	46	186	140	314	1 810	1 496
		(39.74)	(32.31)		(0.92)	(0.42)		(42.94)	(175.47)		(63.49)	(57.25)		(0.3)	(0.45)		(1.01)	(1.32)							
2022	20km	167.95	115.17	-52.78	1	1	0	1 977	1 950	-27	221.6	212.28	-9.32	7.54	7.66	0.12	3	5	2	75	301	226	836	3 590	2 754
		(41.58)	(35.12)		(0.89)	(0.44)		(34.86)	(84.35)		(64.34)	(58.53)		(0.31)	(0.39)		(0.92)	(1.41)							
2022	>20km	171.2	125.37	-45.83	1	1	0	1 974	1 960	-14	220.35	219.76	-0.59	7.68	7.44	-0.24	3	5	2	174	2 086	1 912	4 129	12 963	8 834
		(40.07)	(40.76)		(0.89)	(0.52)		(34.48)	(102.23)		(62.9)	(59.24)		(0.3)	(0.36)		(0.86)	(1.54)							
2023	5km	162.47	112.12	-50.35	1	1	0	1 966	1 930	-36	218.45	212.55	-5.9	7.47	7.62	0.15	3	5	2	40	151	111	412	3 322	2 910
		(40.89)	(34.37)		(1.18)	(0.46)		(38.5)	(80.02)		(65.3)	(59.54)		(0.35)	(0.36)		(0.9)	(1.27)							
2023	10km	171.81	113.43	-58.38	1	1	0	1 967	1 950	-17	229.16	219.17	-9.99	7.58	7.78	0.21	3	5	2	49	197	148	468	2 437	1 969
		(40.13)	(33.98)		(3.41)	(0.44)		(38.71)	(131.08)		(63.13)	(60.17)		(0.32)	(0.43)		(0.85)	(1.33)							
2023	20km	170.32	113.77	-56.55	1	1	0	1 975	1 950	-25	223.26	219.8	-3.46	7.55	7.65	0.1	3	5	2	84	336	252	1 084	5 107	4 023
		(40.9)	(35.62)		(2.06)	(0.45)		(36.09)	(79.78)		(64.63)	(59.07)		(0.32)	(0.39)		(0.88)	(1.44)							
2023	>20km	171.41	122.61	-48.81	1	1	0	1 971	1 960	-11	222.53	224.3	1.77	7.71	7.44	-0.27	3	5	2	177	2 312	2 135	5 563	17 847	12 284
		(41.36)	(39.78)		(20.26)	(0.52)		(36.44)	(79.76)		(63.0)	(59.92)		(0.32)	(0.37)		(0.9)	(1.51)							
2024	5km	160.64	111.98	-48.66	1	1	0	1 954	1 930	-24	222.4	210.36	-12.03	7.47	7.65	0.18	3	5	2	47	152	105	499	3 314	2 815
		(42.49)	(33.76)		(1.15)	(0.46)		(36.52)	(79.94)		(62.46)	(58.63)		(0.34)	(0.37)		(0.94)	(1.27)							
2024	10km	168.54	115.62	-52.92	1	1	0	1 968	1 950	-18	224.06	215.78	-8.29	7.55	7.79	0.24	3	5	2	54	209	155	558	2 564	2 006
		(44.49)	(35.62)		(2.37)	(0.46)		(41.72)	(109.59)		(64.86)	(57.76)		(0.35)	(0.45)		(1.0)	(1.38)							
2024	20km	167.42	115.7	-51.72	1	1	0	1 973	1 950	-23	224.5	218.22	-6.28	7.53	7.66	0.12	3	5	2	87	331	244	1 360	4 751	3 391
		(40.8)	(36.28)		(13.67)	(0.46)		(39.22)	(66.59)		(63.83)	(60.35)		(0.33)	(0.4)		(0.93)	(1.42)							
2024	>20km	169.65	123.73	-45.91	1	1	0	1 969	1 960	-9	219.23	222.84	3.61	7.73	7.43	-0.3	3	5	2	178	2 415	2 237	6 833	17 422	10 589
		(42.23)	(40.88)		(11.62)	(0.53)		(37.07)	(69.11)		(62.64)	(60.17)		(0.33)	(0.39)		(0.91)	(1.56)							

Note. The table reports summary statistics for houses listed for sale within different buffer distances from the France–Belgium border between 2019 and 2024. For each year and buffer, we present the mean or median characteristics of listed properties on each side of the border, along with their differences. Standard deviations are reported in parentheses.

Table 4. Summary statistics – Apartment listed for sale at various buffer distances from the France–Belgium border over time

		Area Mean			Bathrooms Median			Build Year Median			Consoenergie Mean			Ln(Price/Area) Mean			Floor Median			Rooms Median			City Id Nunique			Obs Count		
Year	**Buffer**	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta	Belgium	France	Delta
2019	5km	82.66	71.43	-11.23	1	1	0	1 991	1 979	-12	242.14	204.99	-37.15	7.81	7.65	-0.16	3	2	-1	2	3	1	17	41	24	325	470	145
		(33.42)	(29.3)		(0.65)	(0.34)		(26.12)	(29.84)		(157.05)	(79.57)		(0.34)	(0.37)		(3.31)	(2.01)		(0.91)	(1.12)							
2019	10km	89.4	69.9	-19.5	1	1	0	1 989	1 977	-12	228.42	210.84	-17.58	7.9	7.85	-0.04	2	2	0	2	3	1	24	45	21	668	512	-156
		(35.85)	(27.33)		(0.7)	(0.38)		(20.98)	(83.34)		(138.62)	(84.45)		(0.36)	(0.38)		(2.42)	(2.19)		(0.82)	(1.06)							
2019	20km	87.11	68.29	-18.82	1	1	0	1 999	1 979	-20	211.43	211.92	0.49	7.88	7.85	-0.03	2	2	0	2	3	1	50	51	1	1 344	1 460	116
		(32.82)	(28.16)		(0.62)	(0.4)		(19.31)	(128.64)		(129.49)	(79.6)		(0.41)	(0.38)		(3.06)	(2.15)		(0.83)	(1.12)							
2019	>20km	90.69	67.04	-23.65	1	1	0	1 994	1 974	-20	213.94	235.32	21.37	7.95	7.57	-0.37	2	2	0	2	3	1	145	193	48	6 385	3 839	-2 546
		(33.38)	(27.91)		(0.72)	(0.39)		(22.47)	(149.4)		(126.49)	(92.95)		(0.42)	(0.42)		(3.07)	(1.89)		(0.83)	(1.17)							
2020	5km	80.66	77.91	-2.75	1	1	0	1 990	1 975	-15	239.45	204.2	-35.25	7.89	7.65	-0.24	2	2	0	2	3	1	18	37	19	308	406	98
		(32.25)	(30.2)		(0.49)	(0.34)		(22.51)	(33.09)		(144.62)	(85.48)		(0.31)	(0.36)		(3.5)	(1.9)		(0.87)	(1.12)							
2020	10km	84.49	72.51	-11.98	1	1	0	1 990	1 980	-10	235.32	208.12	-27.2	7.99	7.87	-0.12	3	2	-1	2	3	1	17	47	30	493	436	-57
		(36.14)	(26.01)		(0.62)	(0.33)		(22.67)	(183.02)		(143.98)	(87.93)		(0.36)	(0.44)		(2.44)	(2.49)		(0.77)	(1.03)							
2020	20km	86.44	70.16	-16.28	1	1	0	2 000	1 980	-20	200.37	205.68	5.31	7.95	7.93	-0.01	2	2	0	2	3	1	51	53	2	1 173	1 099	-74
		(33.38)	(26.36)		(0.65)	(0.37)		(20.29)	(163.49)		(125.96)	(84.61)		(0.42)	(0.39)		(3.06)	(2.14)		(0.79)	(1.07)							
2020	>20km	92.62	69.48	-23.14	1	1	0	1 994	1 972	-22	205.93	230.08	24.16	7.99	7.58	-0.41	2	2	0	2	3	1	137	187	50	5 840	2 831	-3 009
		(34.09)	(28.74)		(8.23)	(0.38)		(23.0)	(152.23)		(122.49)	(91.33)		(0.43)	(0.42)		(3.03)	(1.83)		(1.51)	(1.23)							
2021	5km	80.86	74.06	-6.8	1	1	0	1 982	1 987	4	251.76	198.43	-53.33	7.95	7.71	-0.24	3	2	-1	2	3	1	16	42	26	336	511	175
		(34.62)	(29.21)		(0.6)	(0.35)		(27.07)	(31.07)		(140.11)	(75.99)		(0.37)	(0.34)		(3.31)	(2.05)		(0.95)	(1.08)							
2021	10km	87.38	70.05	-17.32	1	1	0	1 993	1 980	-13	228.89	201.61	-27.28	7.99	7.99	-0.0	3	2	-1	2	3	1	17	45	28	616	539	-77
		(34.96)	(24.71)		(0.59)	(0.32)		(22.46)	(28.8)		(147.45)	(89.35)		(0.4)	(0.37)		(2.35)	(2.38)		(0.76)	(0.97)							
2021	20km	86.06	66.92	-19.14	1	1	0	1 999	1 976	-23	213.39	213.17	-0.22	7.92	7.99	0.07	2	2	0	2	3	1	54	48	-6	1 338	1 592	254
		(32.59)	(28.05)		(0.67)	(0.36)		(20.25)	(104.18)		(129.61)	(91.68)		(0.45)	(0.4)		(2.96)	(2.17)		(0.81)	(1.14)							
2021	>20km	93.27	68.62	-24.65	1	1	0	1 995	1 974	-21	203.04	230.71	27.67	8.0	7.68	-0.32	2	2	0	2	3	1	139	183	44	6 615	3 331	-3 284
		(33.79)	(27.98)		(0.69)	(0.35)		(23.56)	(125.32)		(118.99)	(97.15)		(0.42)	(0.42)		(3.9)	(1.86)		(0.79)	(1.22)							
2022	5km	82.04	72.78	-9.26	1	1	0	1 985	1 975	-10	215.21	203.26	-11.95	8.06	7.74	-0.32	3	2	-1	2	3	1	19	43	24	296	609	313
		(33.95)	(29.02)		(0.7)	(0.38)		(27.27)	(30.54)		(121.14)	(77.03)		(0.36)	(0.34)		(3.27)	(2.31)		(0.94)	(1.06)							
2022	10km	89.0	67.76	-21.24	1	1	0	1 990	1 979	-11	218.14	207.23	-10.9	7.99	8.01	0.01	3	1	-2	2	3	1	22	49	27	599	688	89
		(38.38)	(26.05)		(0.57)	(0.38)		(21.65)	(34.8)		(126.63)	(91.95)		(0.39)	(0.4)		(2.27)	(2.5)		(0.83)	(1.03)							
2022	20km	87.71	63.07	-24.64	1	1	0	1 999	1 975	-24	211.94	218.21	6.27	7.94	8.1	0.16	3	2	-1	2	3	1	50	60	10	1 331	2 098	767
		(33.43)	(27.67)		(0.73)	(0.38)		(20.59)	(95.53)		(125.73)	(95.08)		(0.44)	(0.4)		(2.78)	(2.18)		(1.16)	(1.14)							
2022	>20km	92.53	65.37	-27.16	1	1	0	1 995	1 970	-25	199.78	237.38	37.6	8.03	7.75	-0.29	2	2	0	2	3	1	138	217	79	6 346	4 114	-2 232
		(33.45)	(28.45)		(0.67)	(0.43)		(24.36)	(95.44)		(122.68)	(96.92)		(0.41)	(0.48)		(4.43)	(2.09)		(0.79)	(1.19)							
2023	5km	78.9	71.92	-6.98	1	1	0	1 978	1 975	-3	249.02	209.29	-39.72	8.05	7.73	-0.31	4	2	-2	2	3	1	20	54	34	337	913	576
		(34.0)	(29.32)		(0.46)	(0.39)		(31.84)	(66.93)		(135.19)	(86.79)		(0.38)	(0.36)		(3.22)	(2.09)		(0.94)	(1.02)							
2023	10km	94.27	66.99	-27.29	1	1	0	1 990	1 975	-15	210.33	212.71	2.39	8.05	8.02	-0.03	3	2	-1	2	3	1	22	57	35	506	1 141	635
		(40.91)	(26.47)		(0.67)	(0.42)		(29.53)	(64.82)		(131.25)	(86.1)		(0.4)	(0.39)		(2.02)	(2.55)		(0.82)	(1.09)							
2023	20km	86.51	60.07	-26.43	1	1	0	1 999	1 970	-29	196.24	232.09	35.85	8.03	8.12	0.09	3	2	-1	2	3	1	53	71	18	1 351	3 373	2 022
		(33.07)	(27.1)		(0.68)	(0.39)		(21.89)	(77.68)		(120.78)	(106.5)		(0.45)	(0.38)		(2.81)	(2.06)		(0.85)	(1.09)							
2023	>20km	93.46	64.45	-29.01	1	1	0	1 995	1 970	-25	193.17	241.81	48.64	8.08	7.77	-0.32	3	1	-2	2	3	1	140	243	103	5 823	5 618	-205
		(35.04)	(29.29)		(0.7)	(0.45)		(25.99)	(80.17)		(116.39)	(98.44)		(0.43)	(0.5)		(4.98)	(1.92)		(0.82)	(1.24)							
2024	5km	79.58	72.14	-7.44	1	1	0	1 977	1 980	3	237.94	198.11	-39.83	8.04	7.74	-0.29	4	2	-2	2	3	1	17	47	30	382	843	461
		(32.99)	(27.35)		(0.51)	(0.37)		(25.98)	(98.73)		(144.7)	(76.31)		(0.42)	(0.34)		(2.83)	(2.12)		(0.95)	(1.0)							
2024	10km	94.38	68.96	-25.42	1	1	0	1 993	1 979	-14	199.79	207.67	7.88	8.09	8.05	-0.04	4	2	-2	2	3	1	23	52	29	527	1 080	553
		(39.02)	(27.19)		(0.69)	(0.4)		(26.59)	(106.54)		(122.63)	(85.56)		(0.37)	(0.38)		(1.68)	(2.14)		(0.79)	(1.1)							
2024	20km	88.42	62.84	-25.58	1	1	0	1 999	1 971	-28	186.45	220.02	33.57	8.02	8.09	0.07	4	2	-2	2	3	1	53	65	12	1 340	3 019	1 679
		(34.29)	(27.75)		(0.61)	(0.39)		(24.49)	(91.01)		(108.12)	(90.69)		(0.45)	(0.4)		(2.42)	(2.26)		(0.84)	(1.1)							
2024	>20km	91.31	65.46	-25.85	1	1	0	1 992	1 970	-22	187.04	232.63	45.6	8.11	7.8	-0.31	3	2	-1	2	3	1	141	241	100	5 856	5 297	-559
		(33.29)	(29.88)		(5.79)	(0.45)		(29.62)	(79.19)		(110.61)	(93.97)		(0.45)	(0.51)		(2.51)	(1.88)		(0.82)	(1.25)							

Note. The table reports summary statistics for apartments listed for sale within different buffer distances from the France–Belgium border between 2019 and 2024. For each year and buffer, we present the mean or median characteristics of listed properties on each side of the border, along with their differences. Standard deviations are reported in parentheses.

5.4 ML Based Geographic Diff-in-Disc Estimates

Table 5. Coefficient of determination for various η_0 specifications at multiple time period (t) - Full Sample

Period (t)	Lasso Regression	Gradient Boosting (LightGBM)	Linear Regression	Random Forest
2019	24.6 %	22.6 %	-1.4e+27 %	29.4 %
2020	25.2 %	21.5 %	-2.4e+27 %	30.5 %
2021	26.8 %	23.7 %	-8.0e+26 %	31.3 %
2022	20.7 %	25.8 %	-8.9e+26 %	20.8 %
2023	23.8 %	26.6 %	-5.0e+26 %	25.4 %

Note: Observations are restricted to a bandwidth of 10.43km buffer around the border between France and Belgium. This distance buffer is estimated using data-driven optimal bandwidth as described in Calonico, Cattaneo, and Farrell 2020.

Table 6. Coefficient of determination for various η_0 specifications at multiple time period (t) - Energy Intensive Sample

Period (t)	Lasso Regression	Gradient Boosting (LightGBM)	Linear Regression	Random Forest
2019	16.3 %	10.5 %	-2.2e+28 %	19.4 %
2020	15.9 %	8.2 %	-2.7e+28 %	18.7 %
2021	18.4 %	17.0 %	-2.4e+28 %	22.9 %
2022	16.9 %	12.6 %	-2.4e+28 %	20.1 %
2023	21.8 %	14.8 %	-1.2e+28 %	24.0 %

Note: Observations are restricted to a bandwidth of 11.256km buffer around the border between France and Belgium. This distance buffer is estimated using data-driven optimal bandwidth as described in Calonico, Cattaneo, and Farrell 2020.

Table 7. Coefficient of determination for various η_0 specifications at multiple time period (t) - Energy Balanced Sample

Period (t)	Lasso Regression	Gradient Boosting (LightGBM)	Linear Regression	Random Forest
2019	20.2 %	26.3 %	-3.1e+27 %	19.1 %
2020	20.2 %	25.3 %	-2.6e+27 %	22.1 %
2021	19.2 %	23.6 %	-4.4e+27 %	18.9 %
2022	18.4 %	25.0 %	-1.6e+27 %	19.7 %
2023	17.5 %	24.9 %	-6.7e+26 %	22.2 %

Note: Observations are restricted to a bandwidth of 11.020km buffer around the border between France and Belgium. This distance buffer is estimated using data-driven optimal bandwidth as described in Calonico, Cattaneo, and Farrell 2020.

Table 8. Coefficient of determination for various η_0 specifications at multiple time period (t) - Energy Efficient Sample

Period (t)	Lasso Regression	Gradient Boosting (LightGBM)	Linear Regression	Random Forest
2019	26.0 %	30.3 %	-8.5e+27 %	28.5 %
2020	28.3 %	26.7 %	-3.5e+28 %	23.4 %
2021	23.4 %	23.2 %	-4.2e+27 %	15.6 %
2022	24.1 %	22.3 %	-1.9e+28 %	23.3 %
2023	26.2 %	24.2 %	-1.8e+28 %	27.9 %

Note: Observations are restricted to a bandwidth of 13.981km buffer around the border between France and Belgium. This distance buffer is estimated using data-driven optimal bandwidth as described in Calonico, Cattaneo, and Farrell 2020.

Table 9. ML based Geographic Diff-in-Disc Estimates - Full Sample - With Adjustments

Independent Variable:	Natural log of price per square meter - €/m^2									
Running Variable:	Normalized distance to the border (France/Belgium) - Δ^*									
	Panel D: Full Sample									
Period	2019		2020		2021		2022		2023	
First Stage Method: $\tilde{Y}_i(h^*,t) = Y_i(h^*,t) - \hat{\eta}_{0_s}(h^*, Z_i, t)$	(RandomForest)		(RandomForest)		(RandomForest)		(LightGBM)		(LightGBM)	
$\hat{\tau}_t$	0.344***		0.357***		0.334***		0.359***		0.347***	
	(0.0126)		(0.0141)		(0.0125)		(0.0124)		(0.0113)	
Robust Bias-Corrected CI	[0.32, 0.37]		[0.33, 0.38]		[0.31, 0.36]		[0.33, 0.38]		[0.32, 0.37]	
Common Optimal Bandwidth (h^*)	10.430		10.430		10.430		10.430		10.430	
$\hat{\tau}_t^{\text{DIDisc}} = \hat{\tau}_t - \hat{\tau}_{\text{baseline}}$	+1.1pp		+2.3pp		+0.0pp		+2.6pp		+1.3pp	
Bandwidth Position	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Number of Observations	35 731	60 528	31 720	46 860	36 488	50 605	39 438	63 104	46 406	78 633
Number of Unique Obs.	35 731	60 528	31 720	46 860	36 488	50 605	39 438	63 104	46 406	78 633
Number of Effective Obs.	4 918	10 043	4 269	7 798	5 160	9 170	5 824	11 458	6 860	15 108

Note: $\hat{\tau}_t$ denotes the estimated difference in listed prices between France and Belgium at the border at time t. For example, in 2021, asking prices at the border were on average 33.4% higher on the French side than on the Belgian side. This gap did not increased significantly between 2021 and 2022. Standard errors are reported in parentheses. Robust bias-corrected confidence intervals are shown in brackets. All columns use the same optimal bandwidth. "Left" and "Right" denote observations on each side of the France/Belgium border. "pp" refers to percentage-point deviations from the baseline discontinuity. Adjusted estimates use ML-residualized outcomes from the first-stage method listed in the header; unadjusted estimates do not apply any first-stage adjustment.

Table 10. Geographic Diff-in-Disc Estimates - Full Sample - Without Adjustments

Independent Variable:	Natural log of price per square meter - €/m^2									
Running Variable:	Normalized distance to the border (France/Belgium) - Δ^*									
	Panel D: Full Sample									
Period	2019		2020		2021		2022		2023	
No First Stage	(Without Adj.)		(Without Adj.)		(Without Adj.)		(Without Adj.)		(Without Adj.)	
$\hat{\tau}_t$	0.301***		0.281***		0.295***		0.306***		0.245***	
	(0.0146)		(0.0166)		(0.0152)		(0.0142)		(0.0131)	
Robust Bias-Corrected CI	[0.27, 0.33]		[0.25, 0.31]		[0.26, 0.32]		[0.28, 0.33]		[0.22, 0.27]	
Common Optimal Bandwidth $\left(\hat{\Delta}_t^c\right)$	10.430		10.430		10.430		10.430		10.430	
$\hat{\tau}_t^{\text{DIDisc}} = \hat{\tau}_t - \hat{\tau}_{\text{baseline}}$	+0.6pp		-1.3pp		+0.0pp		+1.1pp		-5.0pp*	
Bandwidth Position	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Number of Observations	35 731	60 528	31 720	46 860	36 488	50 605	39 438	63 104	46 406	78 633
Number of Unique Obs.	35 731	60 528	31 720	46 860	36 488	50 605	39 438	63 104	46 406	78 633
Number of Effective Obs.	4 918	10 043	4 269	7 798	5 160	9 170	5 824	11 458	6 860	15 108

Note: $\hat{\tau}_t$ denotes the estimated difference in listed prices between France and Belgium at the border at time t. For example, in 2021, asking prices at the border were on average 29.5% higher on the French side than on the Belgian side. This gap did not increased significantly between 2021 and 2022. Standard errors are reported in parentheses. Robust bias-corrected confidence intervals are shown in brackets. All columns use the same optimal bandwidth. "Left" and "Right" denote observations on each side of the France/Belgium border. "pp" refers to percentage-point deviations from the baseline discontinuity. Adjusted estimates use ML-residualized outcomes from the first-stage method listed in the header; unadjusted estimates do not apply any first-stage adjustment.

Table 11. ML based Geographic Diff-in-Disc Estimates - Energy Intensive Sample - With Adjustments (Second Stage)

Independent Variable:	Natural log of price per square meter - €/m^2									
Running Variable:	Normalized distance to the border (France/Belgium) - Δ^*									
	Panel A: Energy Intensive									
Period	2019		2020		2021		2022		2023	
First Stage Method: $\tilde{Y}_i(h^*,t) = Y_i(h^*,t) - \hat{\eta}_{0_s}(h^*, Z_i, t)$	(RandomForest)		(RandomForest)		(RandomForest)		(RandomForest)		(RandomForest)	
$\hat{\tau}_t$	0.319***		0.320***		0.361***		0.253***		0.242***	
	(0.0421)		(0.0565)		(0.0382)		(0.0318)		(0.0281)	
Robust Bias-Corrected CI	[0.24, 0.40]		[0.21, 0.43]		[0.29, 0.44]		[0.19, 0.32]		[0.19, 0.30]	
Common Optimal Bandwidth (h^*)	11.256		11.256		11.256		11.256		11.256	
$\hat{\tau}_t^{\text{DIDisc}} = \hat{\tau}_t - \hat{\tau}_{\text{baseline}}$	-4.2pp		-4.2pp		+0.0pp		-10.8pp*		-11.9pp*	
Bandwidth Position	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Number of Observations	16 194	7 329	13 236	5 247	14 955	6 378	16 829	9 782	18 584	11 471
Number of Unique Obs.	16 194	7 329	13 236	5 247	14 955	6 378	16 829	9 782	18 584	11 471
Number of Effective Obs.	2 612	698	2 267	546	2 629	718	3 057	1 219	3 412	1 614

Note: $\hat{\tau}_t$ denotes the estimated difference in listed prices of for energy-intensive properties between France and Belgium at the border. For example, in 2021, asking prices at the border were on average 36.1% higher on the French side than on the Belgian side. This gap decreased significantly between 2021 and 2022 (-10.8pp). Standard errors are reported in parentheses. Robust bias-corrected confidence intervals are shown in brackets. All columns use the same optimal bandwidth. "Left" and "Right" denote observations on each side of the France/Belgium border. "pp" refers to percentage-point deviations from the baseline discontinuity. Adjusted estimates use ML-residualized outcomes from the first-stage method listed in the header; unadjusted estimates do not apply any first-stage adjustment.

Table 12. Geographic Diff-in-Disc Estimates - Energy Intensive Sample - Without Adjustment

Independent Variable:	Natural log of price per square meter - €/m^2									
Running Variable:	Normalized distance to the border (France/Belgium) - Δ^*									
	Panel A: Energy Intensive									
Period	2019		2020		2021		2022		2023	
No First Stage	(Without Adj.)		(Without Adj.)		(Without Adj.)		(Without Adj.)		(Without Adj.)	
$\hat{\tau}_t$	0.356***		0.265***		0.337***		0.242***		0.188***	
	(0.0519)		(0.0605)		(0.0452)		(0.0371)		(0.0356)	
Robust Bias-Corrected CI	[0.25, 0.46]		[0.15, 0.38]		[0.25, 0.43]		[0.17, 0.31]		[0.12, 0.26]	
Common Optimal Bandwidth $\left(\hat{\Delta}_t^c\right)$	11.256		11.256		11.256		11.256		11.256	
$\hat{\tau}_t^{\text{DIDisc}} = \hat{\tau}_t - \hat{\tau}_{\text{baseline}}$	+1.9pp		-7.2pp		+0.0pp		-9.5pp		-14.9pp**	
Bandwidth Position	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Number of Observations	16 194	7 329	13 236	5 247	14 955	6 378	16 829	9 782	18 584	11 471
Number of Unique Obs.	16 194	7 329	13 236	5 247	14 955	6 378	16 829	9 782	18 584	11 471
Number of Effective Obs.	2 612	698	2 267	546	2 629	718	3 057	1 219	3 412	1 614

Note: $\hat{\tau}_t$ denotes the estimated difference in listed prices of for energy-intensive properties between France and Belgium at the border at time t. For example, in 2021, asking prices at the border were on average 33.7% higher on the French side than on the Belgian side. This gap did not change significantly between 2021 and 2022. Standard errors are reported in parentheses. Robust bias-corrected confidence intervals are shown in brackets. All columns use the same optimal bandwidth. "Left" and "Right" denote observations on each side of the France/Belgium border. "pp" refers to percentage-point deviations from the baseline discontinuity. Adjusted estimates use ML-residualized outcomes from the first-stage method listed in the header; unadjusted estimates do not apply any first-stage adjustment.

Table 13. ML based Geographic Diff-in-Disc Estimates - Energy Balanced Sample - With Adjustments

Independent Variable:	Natural log of price per square meter - €/m^2									
Running Variable:	Normalized distance to the border (France/Belgium) - Δ^*									
	Panel B: Energy Balanced									
Period	2019		2020		2021		2022		2023	
First Stage Method: $\tilde{Y}_i(h^*,t) = Y_i(h^*,t) - \hat{\eta}_{0,s}(h^*, Z_i, t)$	(LightGBM)		(LightGBM)		(LightGBM)		(LightGBM)		(LightGBM)	
$\hat{\tau}_t$	0.260***		0.313***		0.308***		0.308***		0.292***	
	(0.0155)		(0.0177)		(0.0166)		(0.0157)		(0.0142)	
Robust Bias-Corrected CI	[0.23, 0.29]		[0.28, 0.35]		[0.27, 0.34]		[0.28, 0.34]		[0.26, 0.32]	
Common Optimal Bandwidth (h^*)	11.020		11.020		11.020		11.020		11.020	
$\hat{\tau}_t^{\text{DIDisc}} = \hat{\tau}_t - \hat{\tau}_{\text{baseline}}$	-4.8pp*		+0.5pp		+0.0pp		+0.0pp		-1.6pp	
Bandwidth Position	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Number of Observations	17 673	50 215	16 369	38 829	18 999	41 146	19 899	50 135	23 996	63 584
Number of Unique Obs.	17 673	50 215	16 369	38 829	18 999	41 146	19 899	50 135	23 996	63 584
Number of Effective Obs.	2 398	9 502	2 061	7 283	2 620	8 519	2 847	10 502	3 482	13 968

Note: $\hat{\tau}_t$ denotes the estimated difference in listed prices of for energy-balanced properties between France and Belgium at the border at time t. For example, in 2021, asking prices at the border were on average 30.8% higher on the French side than on the Belgian side. This gap did not change significantly between 2021 and 2022. Standard errors are reported in parentheses. Robust bias-corrected confidence intervals are shown in brackets. All columns use the same optimal bandwidth. "Left" and "Right" denote observations on each side of the France/Belgium border. "pp" refers to percentage-point deviations from the baseline discontinuity. Adjusted estimates use ML-residualized outcomes from the first-stage method listed in the header; unadjusted estimates do not apply any first-stage adjustment.

Table 14. Geographic Diff-in-Disc Estimates - Energy Balanced Sample - Without Adjustment

Independent Variable:	Natural log of price per square meter - €/m^2									
Running Variable:	Normalized distance to the border (France/Belgium) - Δ^*									
	Panel B: Energy Balanced									
Period	2019		2020		2021		2022		2023	
No First Stage	(Without Adj.)		(Without Adj.)		(Without Adj.)		(Without Adj.)		(Without Adj.)	
$\hat{\tau}_t$	0.136***		0.162***		0.180***		0.181***		0.103***	
	(0.0182)		(0.0203)		(0.0187)		(0.0178)		(0.0163)	
Robust Bias-Corrected CI	[0.10, 0.17]		[0.12, 0.20]		[0.14, 0.22]		[0.15, 0.22]		[0.07, 0.13]	
Common Optimal Bandwidth $\left(\hat{\Delta}_t^c\right)$	11.020		11.020		11.020		11.020		11.020	
$\hat{\tau}_t^{\text{DIDisc}} = \hat{\tau}_t - \hat{\tau}_{\text{baseline}}$	-4.4pp		-1.8pp		+0.0pp		+0.1pp		-7.8pp**	
Bandwidth Position	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Number of Observations	17 673	50 215	16 369	38 829	18 999	41 146	19 899	50 135	23 996	63 584
Number of Unique Obs.	17 673	50 215	16 369	38 829	18 999	41 146	19 899	50 135	23 996	63 584
Number of Effective Obs.	2 398	9 502	2 061	7 283	2 620	8 519	2 847	10 502	3 482	13 968

Note: $\hat{\tau}_t$ denotes the estimated difference in listed prices of for energy-balanced properties between France and Belgium at the border at time t. For example, in 2021, asking prices at the border were on average 18% higher on the French side than on the Belgian side. This gap did not change significantly between 2021 and 2022. Standard errors are reported in parentheses. Robust bias-corrected confidence intervals are shown in brackets. All columns use the same optimal bandwidth. "Left" and "Right" denote observations on each side of the France/Belgium border. "pp" refers to percentage-point deviations from the baseline discontinuity. Adjusted estimates use ML-residualized outcomes from the first-stage method listed in the header; unadjusted estimates do not apply any first-stage adjustment.

Table 15. ML based Geographic Diff-in-Disc Estimates - Energy Efficient Sample - With Adjustments

Independent Variable:	Natural log of price per square meter - €/m^2									
Running Variable:	Normalized distance to the border (France/Belgium) - Δ^*									
	Panel C: Energy Efficient									
Period	2019		2020		2021		2022		2023	
First Stage Method: $\tilde{Y}_i(h^*,t) = Y_i(h^*,t) - \hat{\eta}_{0_s}(h^*, Z_i, t)$	(LightGBM)		(Lasso)		(Lasso)		(Lasso)		(RandomForest)	
$\hat{\tau}_t$	0.181**		0.219***		0.218***		0.247***		0.207***	
	(0.0595)		(0.0493)		(0.0509)		(0.0470)		(0.0393)	
Robust Bias-Corrected CI	[0.06, 0.30]		[0.12, 0.32]		[0.12, 0.32]		[0.15, 0.34]		[0.13, 0.28]	
Common Optimal Bandwidth (h^*)	13.981		13.981		13.981		13.981		13.981	
$\hat{\tau}_t^{\text{DIDisc}} = \hat{\tau}_t - \hat{\tau}_{\text{baseline}}$	-3.7pp		+0.0pp		+0.0pp		+2.9pp		-1.2pp	
Bandwidth Position	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Number of Observations	1 864	2 984	2 115	2 784	2 534	3 081	2 710	3 187	3 826	3 578
Number of Unique Obs.	1 864	2 984	2 115	2 784	2 534	3 081	2 710	3 187	3 826	3 578
Number of Effective Obs.	334	1 072	371	959	390	1 157	413	1 200	656	1 370

Note: $\hat{\tau}_t$ denotes the estimated difference in listed prices of for energy-efficient properties between France and Belgium at the border at time t. For example, in 2021, asking prices at the border were on average 21.8% higher on the French side than on the Belgian side. This gap did not change significantly between 2021 and 2022. Standard errors are reported in parentheses. Robust bias-corrected confidence intervals are shown in brackets. All columns use the same optimal bandwidth. "Left" and "Right" denote observations on each side of the France/Belgium border. "pp" refers to percentage-point deviations from the baseline discontinuity. Adjusted estimates use ML-residualized outcomes from the first-stage method listed in the header; unadjusted estimates do not apply any first-stage adjustment.

Table 16. Geographic Diff-in-Disc Estimates - Energy Efficient Sample - Without Adjustment

Independent Variable:	Natural log of price per square meter - €/m^2									
Running Variable:	Normalized distance to the border (France/Belgium) - Δ^*									
	Panel C: Energy Efficient									
Period	2019		2020		2021		2022		2023	
No First Stage	(Without Adj.)		(Without Adj.)		(Without Adj.)		(Without Adj.)		(Without Adj.)	
$\hat{\tau}_t$	-0.085.		-0.104*		0.004		0.003		0.064	
	(0.0546)		(0.0567)		(0.0583)		(0.0550)		(0.0447)	
Robust Bias-Corrected CI	[-0.19, 0.02]		[-0.22, 0.01]		[-0.11, 0.12]		[-0.10, 0.11]		[-0.02, 0.15]	
Common Optimal Bandwidth $\left(\hat{\Delta}_t^c\right)$	13.981		13.981		13.981		13.981		13.981	
$\hat{\tau}_t^{\text{DIDisc}} = \hat{\tau}_t - \hat{\tau}_{\text{baseline}}$	-8.9pp		-10.8pp		+0.0pp		-0.0pp		+6.0pp	
Bandwidth Position	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Number of Observations	1 864	2 984	2 115	2 784	2 534	3 081	2 710	3 187	3 826	3 578
Number of Unique Obs.	1 864	2 984	2 115	2 784	2 534	3 081	2 710	3 187	3 826	3 578
Number of Effective Obs.	334	1 072	371	959	390	1 157	413	1 200	656	1 370

Note: $\hat{\tau}_t$ denotes the estimated difference in listed prices of for energy-efficient properties between France and Belgium at the border at time t. For example, in 2021, asking prices at the border were on average 0.4% higher on the French side than on the Belgian side. This gap did not change significantly between 2021 and 2022. Standard errors are reported in parentheses. Robust bias-corrected confidence intervals are shown in brackets. All columns use the same optimal bandwidth. "Left" and "Right" denote observations on each side of the France/Belgium border. "pp" refers to percentage-point deviations from the baseline discontinuity. Adjusted estimates use ML-residualized outcomes from the first-stage method listed in the header; unadjusted estimates do not apply any first-stage adjustment.

5.5 Mapping Non-Disclosure

Figure 13. Share of non-compliers (properties listed without an EPC score) at multiple point in time

(a) Apartments Up for Sale (Full Sample)

(b) Houses Up for Sale (Full sample)

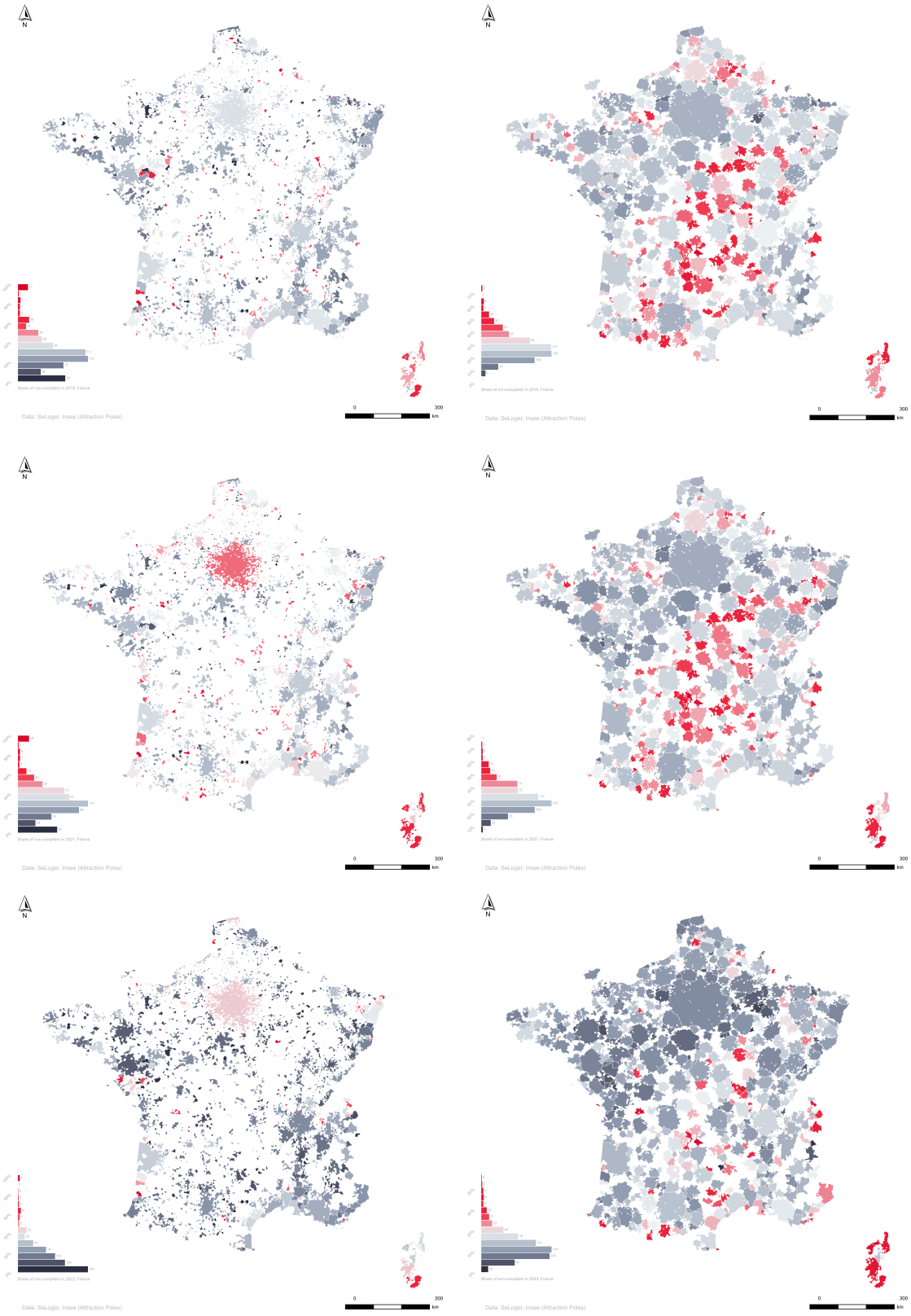
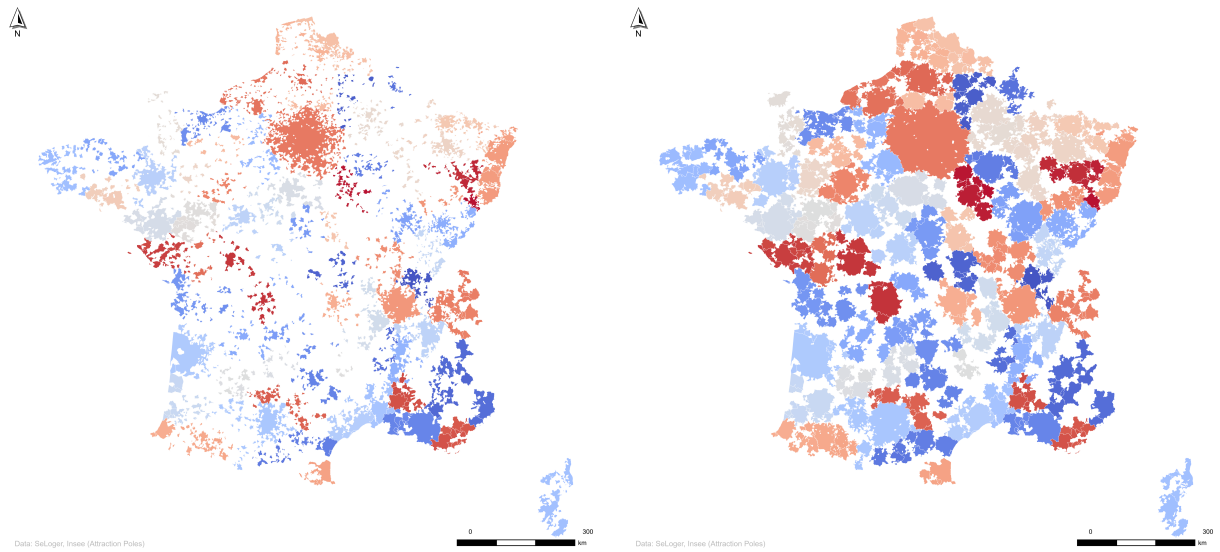


Figure 14. City influence INSEE clusters against available SeLoger data (2018-2024)

(a) Apartments Up for Sale (Full Sample) **(b)** Houses Up for Sale (Full sample)



Note: Each polygon corresponds to an INSEE "city influence" cluster, and the color shading is used solely to differentiate clusters from one another. The maps display which clusters contain SeLoger listings for apartments (Panel a) and houses (Panel b) across France, illustrating the geographic coverage of the available data

5.6 Estimating Green Premia Dynamics

To enhance the stability of the estimated price indices $I(\text{EPC}, g, t)$ and to minimize potential model misspecification arising from the encoding of time fixed effects, we adopt a *quarterly temporal aggregation* in the baseline regression. Estimating the model at a quarterly frequency ensures a sufficient number of observations per period, thereby improving the representativeness of each time dummy T_i and mitigating the risk of overfitting or noise driven by sparse monthly data. This approach stabilizes the estimation of the time coefficients γ_t, which capture the underlying temporal evolution of housing prices within each energy performance category and local market.

$$I(\text{EPC}, g, t) : \begin{cases} \ln(p_i)|_{(\text{EPC},g)} = \gamma_0 + \sum_{k=1}^{K} \beta_k X_{ik} + \gamma_t \cdot T_i + \epsilon_i, \\ \\ I\left(\text{EPC}, g, t \neq 0\right) = 100 \times \exp(\widehat{\gamma}_t), \\ I\left(\text{EPC}, g, t = 0\right) = 100. \end{cases} \tag{Eq. 7}$$

where p_i denotes the price per square meter of listing i, X_i is a vector of structural and locational characteristics (e.g., number of rooms, floor level, proximity to the city center...), and T_i represents the time dummy associated with the quarter t.

To further smooth short-term volatility and improve the robustness of γ_t, we implement a *temporal shift and averaging procedure*. Specifically, the regression is re-estimated twice: once after shifting the time dummies T_i forward by one month and once after shifting them backward by one month relative to the baseline specification. The resulting coefficients $\gamma_t^{(+1)}$ and $\gamma_t^{(-1)}$ are then averaged with the original quarterly coefficients $\gamma_t^{(0)}$, yielding smoothed estimates:

$$\widehat{\gamma}_t = \frac{1}{3}\left(\gamma_t^{(-1)} + \gamma_t^{(0)} + \gamma_t^{(+1)}\right). \tag{Eq. 8}$$

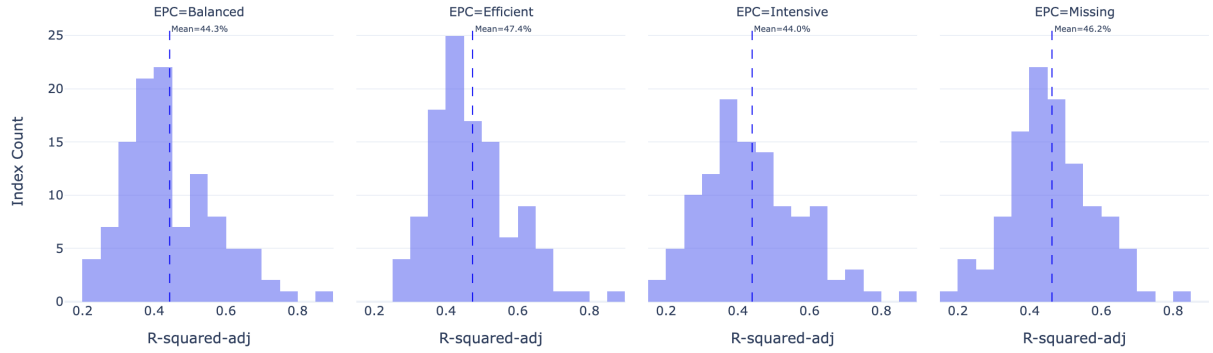
This procedure allows us to transform the quarterly estimates into a *monthly frequency index* while reducing the influence of month-to-month idiosyncratic shocks or irregularities in the listing data. By construction, this

smoothing preserves the medium-term dynamics of housing prices while filtering out high-frequency noise that may stem from data seasonality, reporting delays, or transient market conditions (see similar smoothing strategies in Bailey, Muth, and Nourse 1963; Geltner 1993).

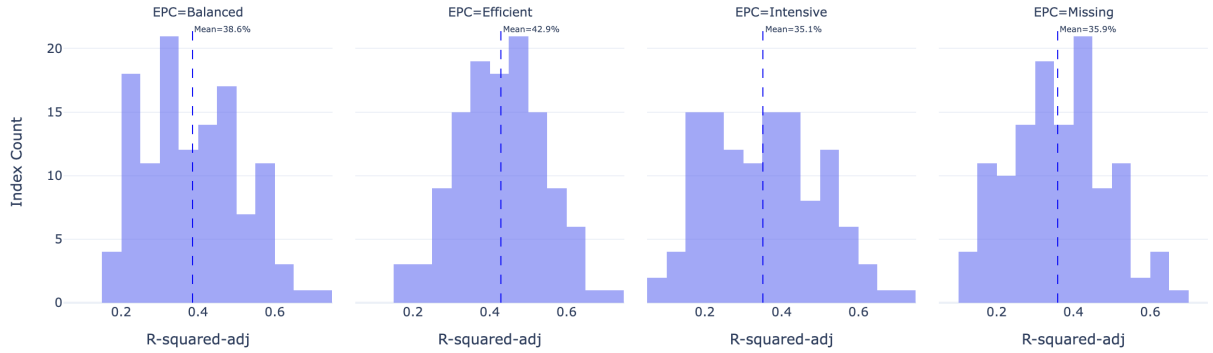
Consequently, the resulting indices $I(\text{EPC}, g, t)$ provide a more stable and reliable measure of local housing price evolution across energy performance groups, while maintaining temporal resolution sufficient for the analysis of policy effects and dynamic responses.

Figure 15. Distribution of adjusted R^2 from cluster-level hedonic regressions by energy consumption category

Market for Apartments



Market for Houses



Note: This figure shows the distribution of adjusted R-squared values from cluster-level hedonic price regressions, estimated separately by energy consumption category (Balanced, Efficient, Intensive, and Missing). The top panel corresponds to the apartment market, while the bottom panel corresponds to the housing market. Each histogram displays the distribution across spatial clusters; the dashed vertical line indicates the mean adjusted R-squared within each energy consumption group across clusters.

Table 17. Descriptive statistics per energy consumption levels over years (predicted listed price per square meter over clusters)

Panel A : *Hedonic listed price per square meter (€/m^2) of houses up for sale between 2018 and 2024 per energy consumption level (SeLoger, France - Insee Clusters)*

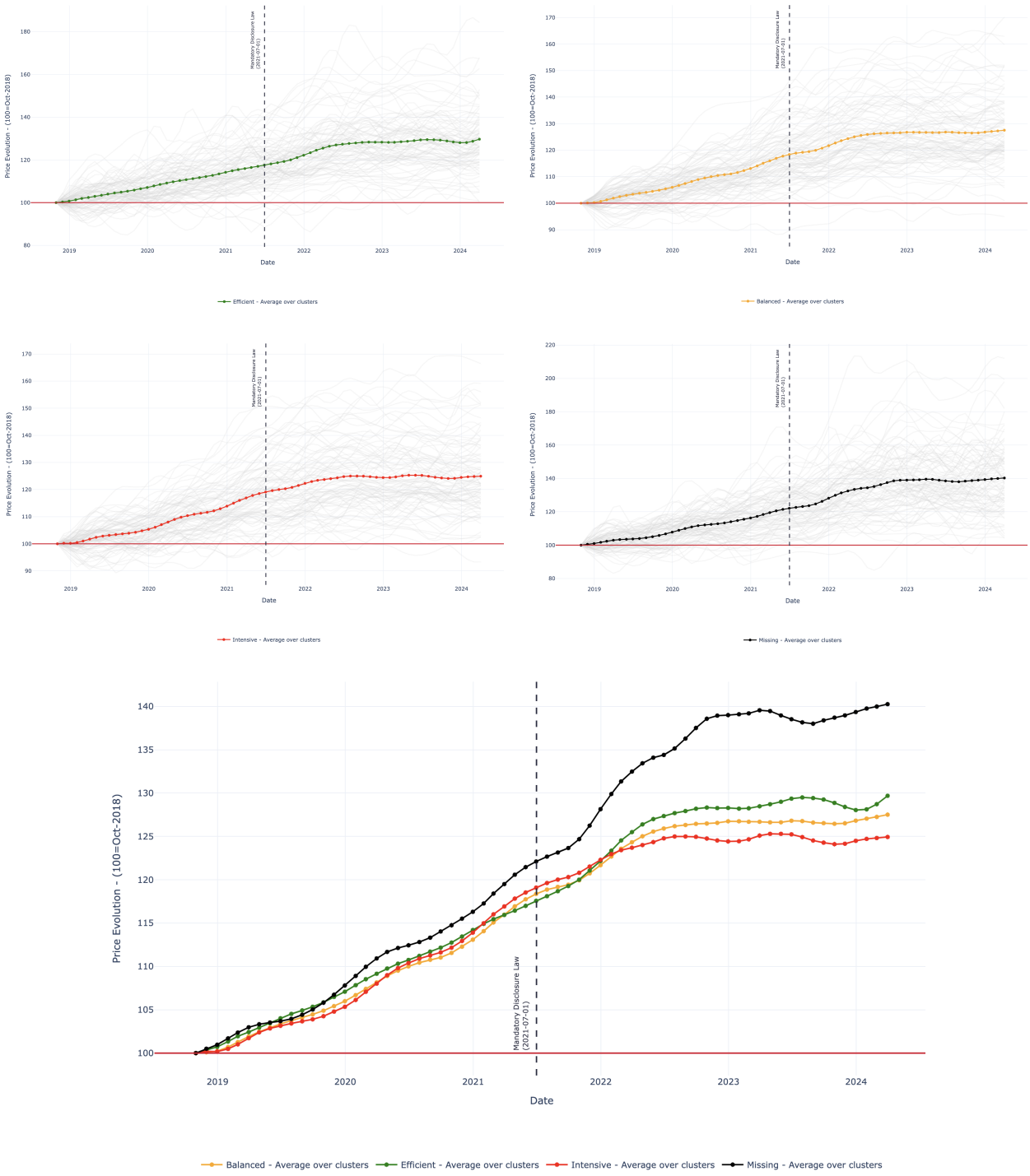
	Mean				Percentile (25%)				Median				Percentile (75%)			
Years	Balanced	Efficient	Intensive	Missing	Balanced	Efficient	Intensive	Missing	Balanced	Efficient	Intensive	Missing	Balanced	Efficient	Intensive	Missing
2018	1 681	1 771	1 580	1 628	1 143	1 181	1 101	1 078	1 548	1 695	1 487	1 538	1 979	2 235	1 930	1 956
2019	1 709	1 815	1 615	1 664	1 164	1 210	1 131	1 119	1 568	1 753	1 500	1 573	2 018	2 310	2 000	2 013
2020	1 790	1 908	1 688	1 751	1 207	1 265	1 180	1 172	1 644	1 833	1 556	1 638	2 137	2 379	2 074	2 131
2021	1 922	2 052	1 790	1 893	1 267	1 351	1 235	1 268	1 769	1 944	1 653	1 773	2 349	2 595	2 179	2 381
2022	2 024	2 183	1 850	1 980	1 316	1 455	1 284	1 321	1 852	2 075	1 706	1 861	2 470	2 715	2 292	2 483
2023	2 031	2 206	1 829	1 964	1 331	1 474	1 273	1 317	1 866	2 091	1 678	1 819	2 501	2 791	2 278	2 458
2024	2 030	2 213	1 824	1 980	1 349	1 481	1 259	1 326	1 847	2 099	1 683	1 785	2 529	2 800	2 224	2 530

Panel B : *Hedonic listed price per square meter (€/m^2) of apartments up for sale between 2018 and 2024 per energy consumption level (SeLoger, France - Insee Clusters)*

	Mean				Percentile (25%)				Median				Percentile (75%)			
Year	Balanced	Efficient	Intensive	Missing	Balanced	Efficient	Intensive	Missing	Balanced	Efficient	Intensive	Missing	Balanced	Efficient	Intensive	Missing
2018	1 875	2 012	1 910	2 116	1 296	1 455	1 280	1 345	1 693	1 796	1 696	1 794	2 155	2 332	2 169	2 507
2019	1 931	2 082	1 965	2 195	1 361	1 485	1 313	1 404	1 745	1 865	1 706	1 876	2 231	2 381	2 240	2 574
2020	2 052	2 222	2 102	2 364	1 424	1 551	1 386	1 508	1 879	1 995	1 783	2 061	2 396	2 538	2 472	2 736
2021	2 198	2 365	2 263	2 561	1 525	1 634	1 455	1 630	2 013	2 132	1 967	2 309	2 561	2 743	2 692	3 019
2022	2 332	2 525	2 362	2 805	1 591	1 767	1 490	1 786	2 145	2 296	2 057	2 561	2 721	2 947	2 850	3 359
2023	2 346	2 565	2 363	2 872	1 604	1 814	1 496	1 837	2 177	2 329	2 055	2 640	2 769	3 039	2 804	3 434
2024	2 358	2 589	2 363	2 975	1 637	1 854	1 495	1 963	2 175	2 372	2 048	2 694	2 815	3 081	2 777	3 581

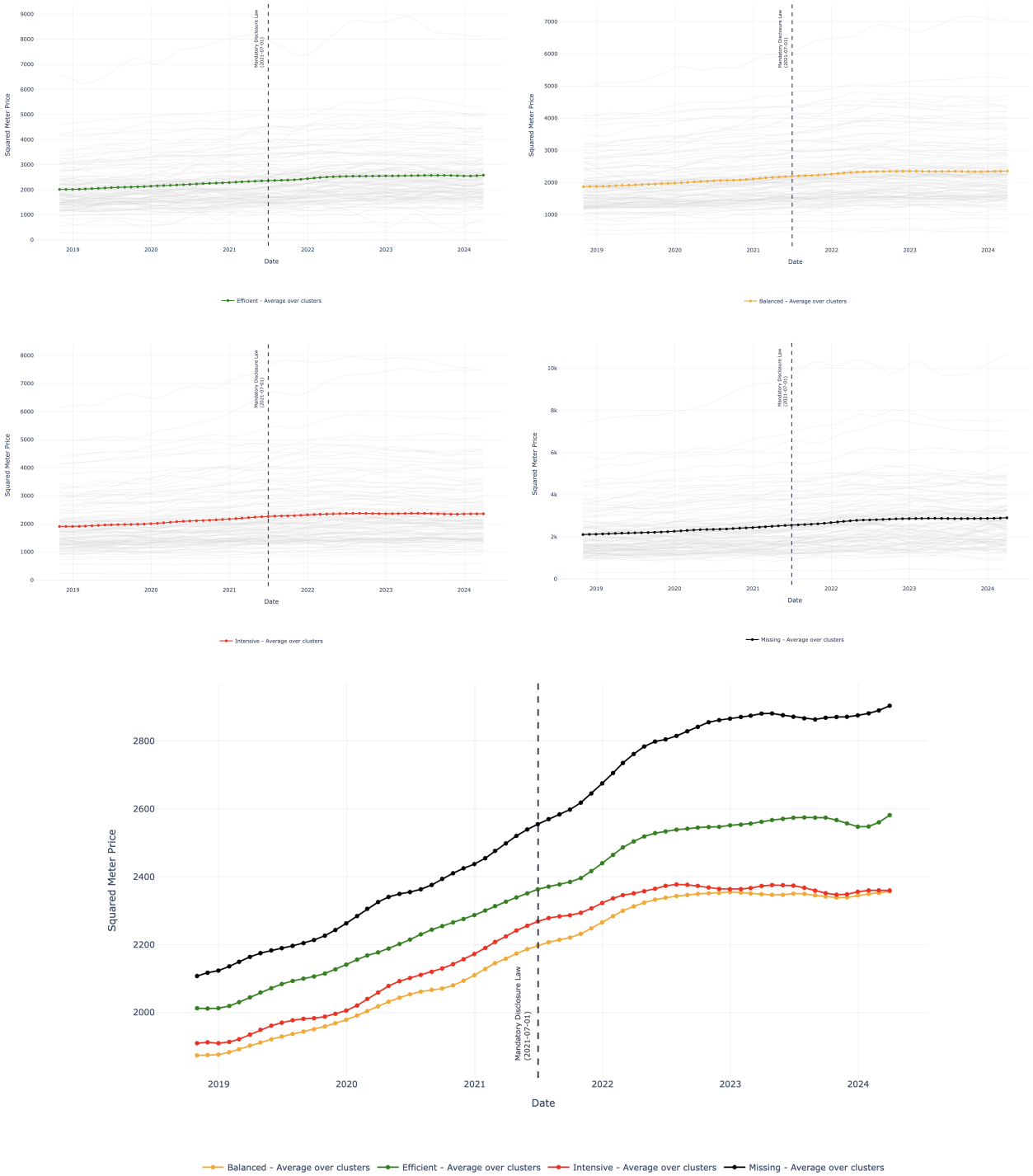
Note: The table reports, for each year between 2018 and 2024, the summary statistics derived from our hedonic pricing regressions for houses (Panel A) and apartments (Panel B) over INSEE clusters. For every energy-consumption category, we present the estimated hedonic square-meter price (mean) together with the 25th percentile, median, and 75th percentile of the predicted price distribution. These model-based values, computed using the SeLoger dataset and INSEE cluster definitions, document how predicted prices evolve over time across energy-efficiency groups.

Figure 16. Cluster-level hedonic monthly apartment indices and unweighted averages by EPC group (100 = Oct-2018)



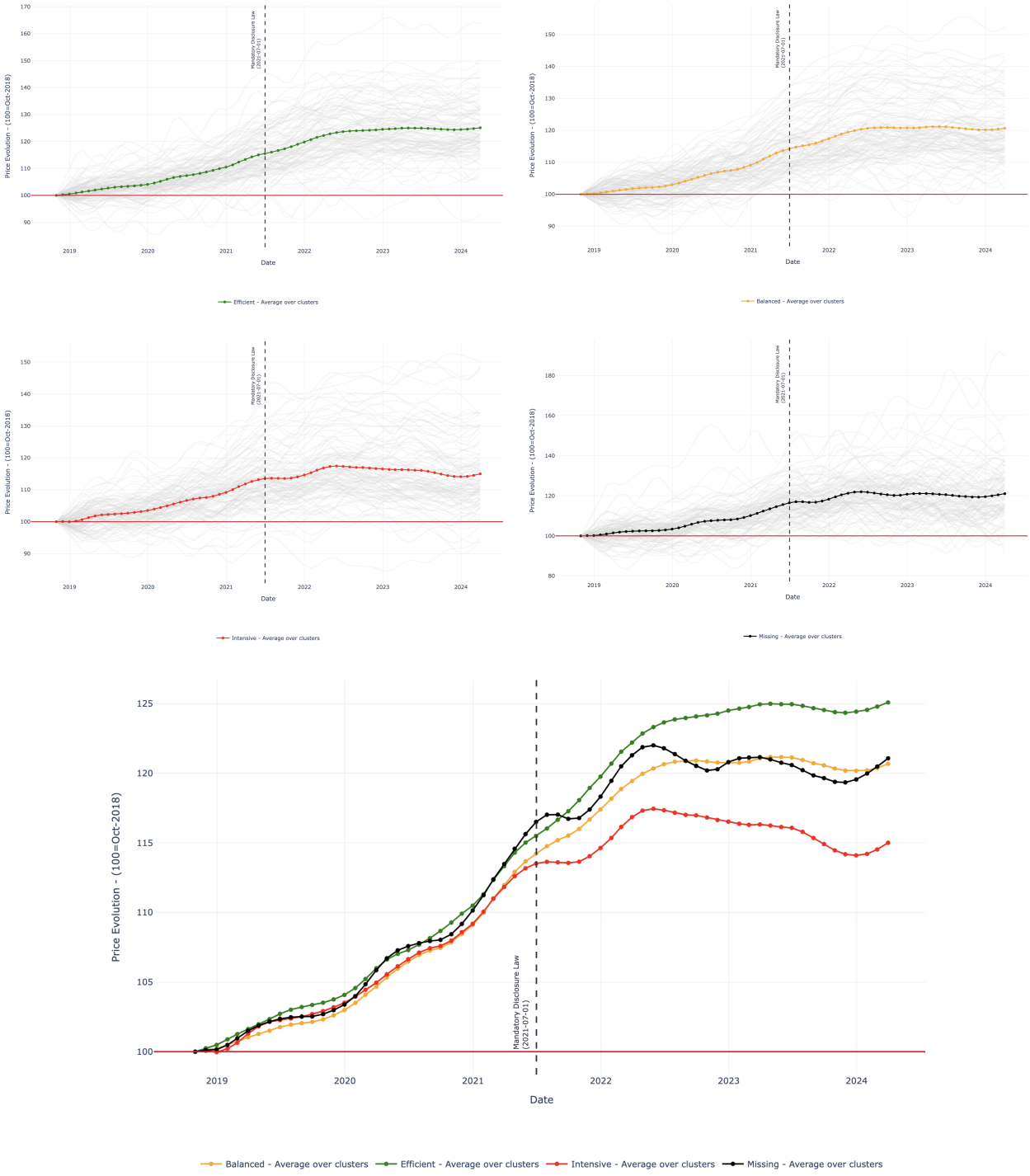
Note: The indices are constructed using the two-step hedonic estimation procedure described in Section 3.2.1. Each line traces the monthly evolution of the predicted price of a reference apartment within each INSEE cluster, grouped by EPC category. The colored lines show the unweighted average index across clusters for each EPC group (normalized to 100 in October 2018), illustrating how price dynamics differ across energy-consumption categories over time.

Figure 17. Cluster-level hedonic monthly apartment prices and unweighted averages by EPC group



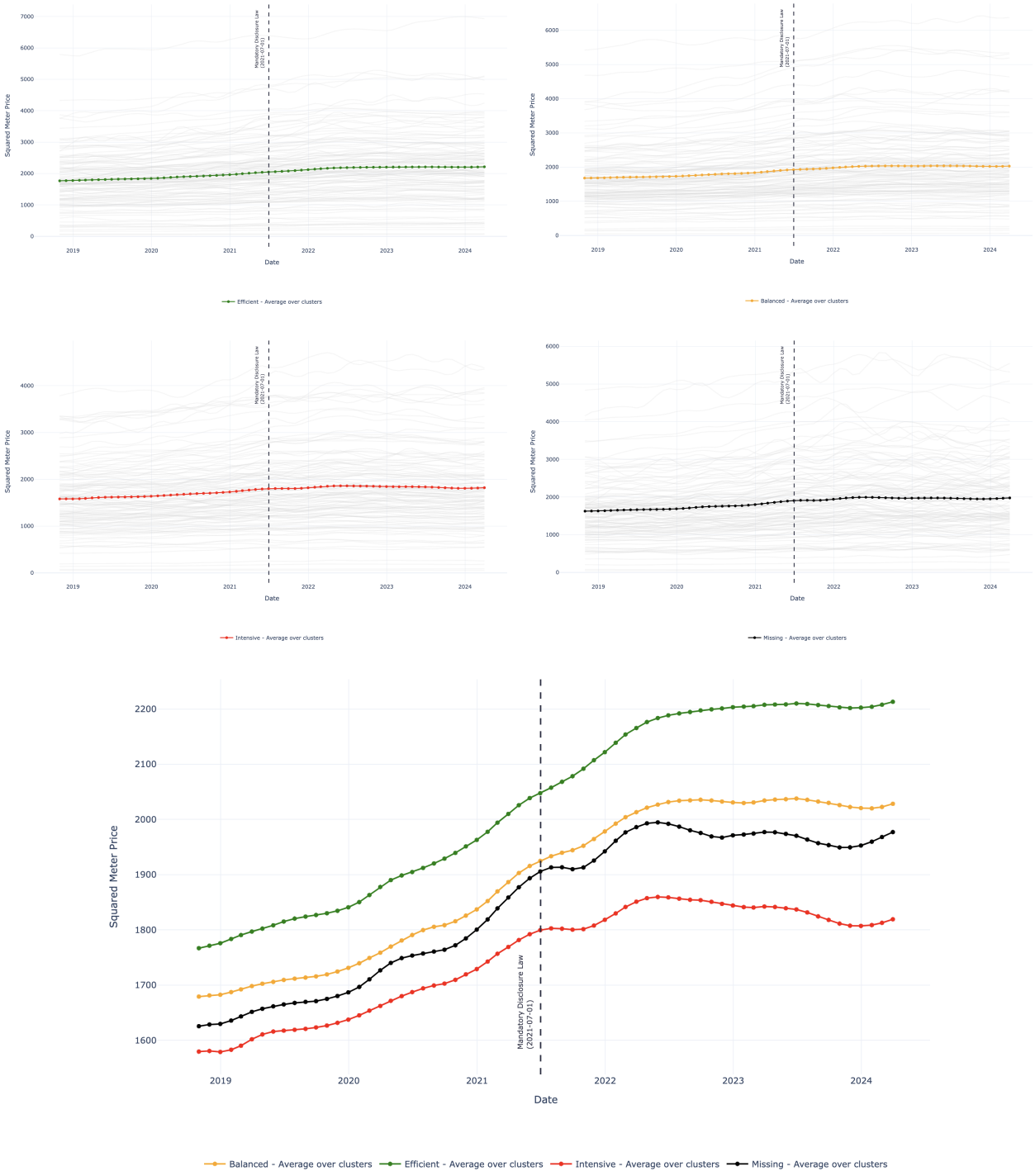
Note. The series are obtained using the two-step hedonic estimation procedure described in Section 3.2.1. Each line shows the monthly predicted square-meter price of a reference apartment within each INSEE cluster, grouped by EPC category. The colored lines plot the unweighted average price levels across clusters for each EPC group, illustrating how predicted apartment prices evolve over time across energy-consumption categories.

Figure 18. Cluster-level hedonic monthly house indices and unweighted averages by EPC group (100 = Oct-2018)



Note: The indices are constructed using the two-step hedonic estimation procedure described in Section 3.2.1. Each line traces the monthly evolution of the predicted price of a reference house within each INSEE cluster, grouped by EPC category. The colored lines show the unweighted average index across clusters for each EPC group (normalized to 100 in October 2018), illustrating how price dynamics differ across energy-consumption categories over time.

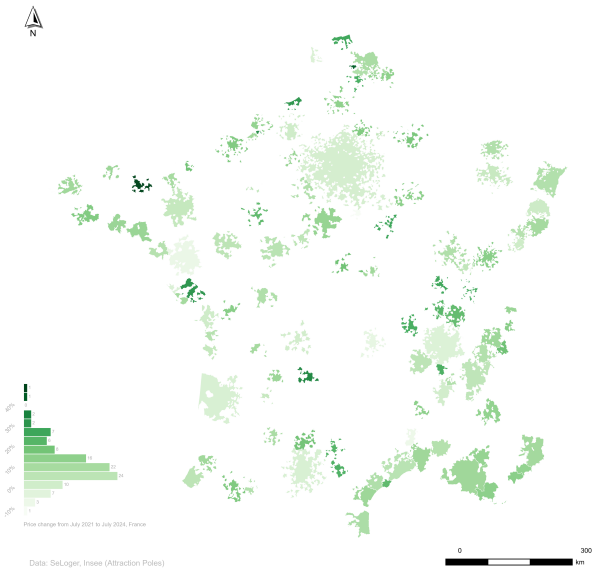
Figure 19. Cluster-level hedonic monthly house prices and unweighted averages by EPC group



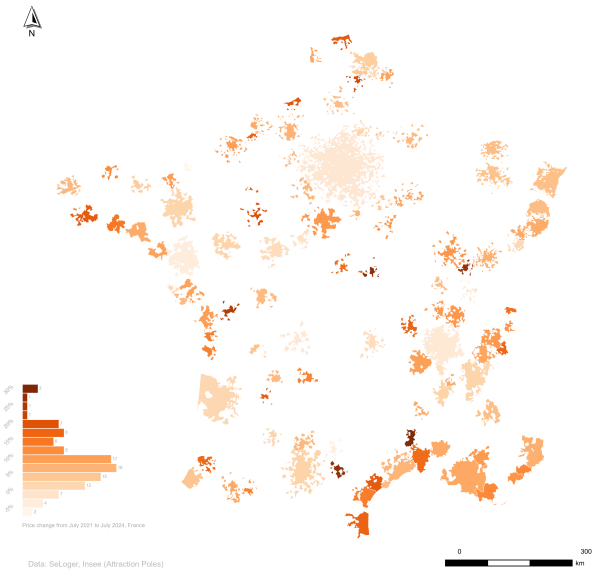
Note. The series are obtained using the two-step hedonic estimation procedure described in Section 3.2.1. Each line shows the monthly predicted square-meter price of a reference house within each INSEE cluster, grouped by EPC category. The colored lines plot the unweighted average price levels across clusters for each EPC group, illustrating how predicted apartment prices evolve over time across energy-consumption categories.

Figure 20. Hedonic price variations of the reference property per cluster and energy consumption level between July 2021 and July 2024 (Apartments up for sale)

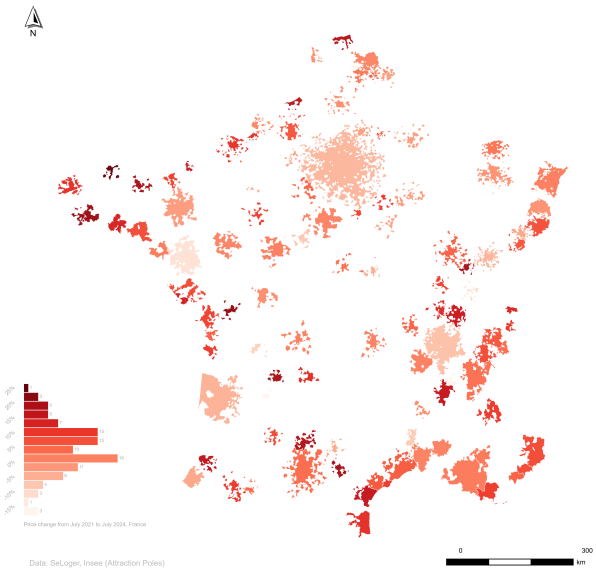
(a) Energy Efficient Apartments



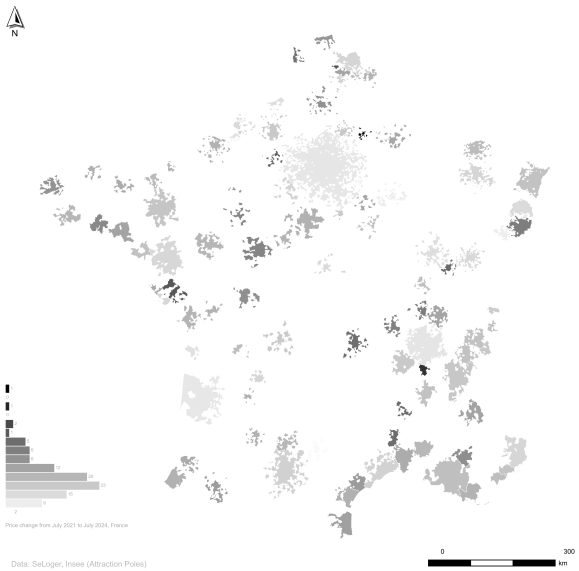
(b) Energy Balanced Apartments



(c) Energy Efficient Apartments



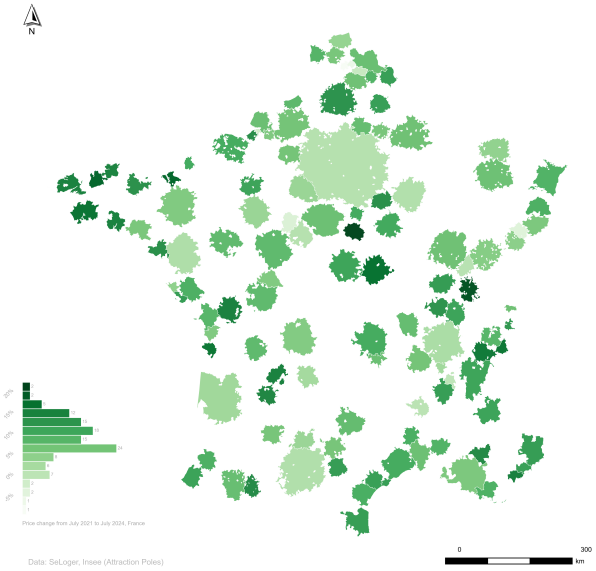
(d) Apartments listed without an EPC score



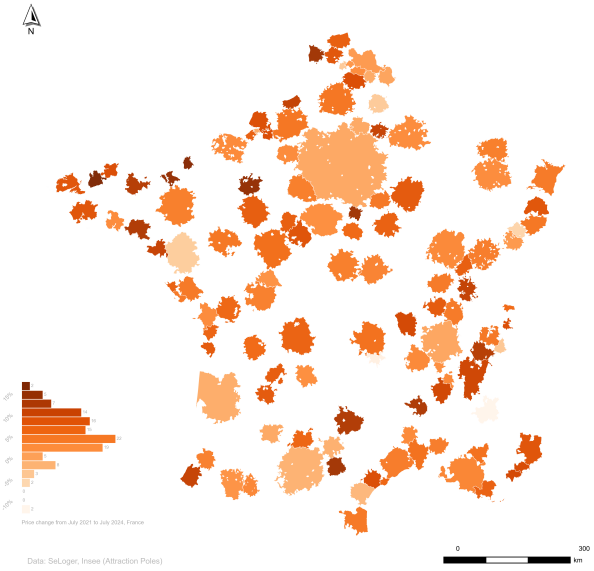
Note: Each map reports the estimated change in the hedonic price of a reference apartment between July 2021 and July 2024 across INSEE clusters, shown separately by energy-consumption category. Colors distinguish the direction and relative intensity of the predicted price variation produced by our hedonic model. The panels correspond to (a) energy-efficient apartments, (b) energy-balanced apartments, (c) energy-intensive apartments, and (d) listings without an EPC score, illustrating how predicted prices evolved spatially over the period.

Figure 21. Hedonic price variations of the reference property per cluster and energy consumption level between July 2021 and July 2024 (Houses up for sale)

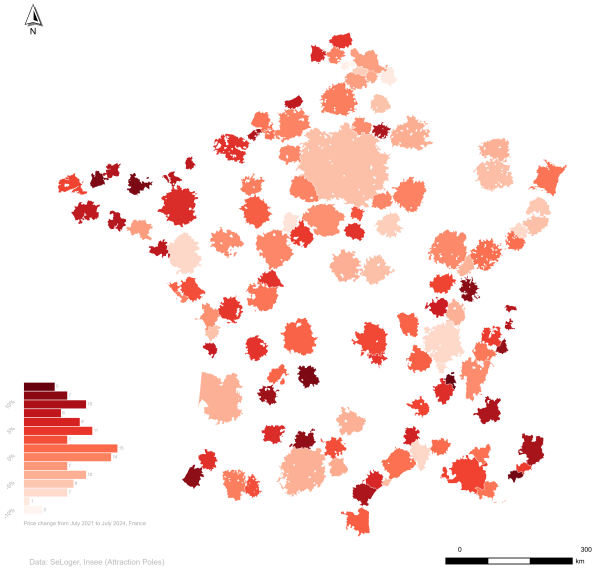
(a) Energy Efficient Houses



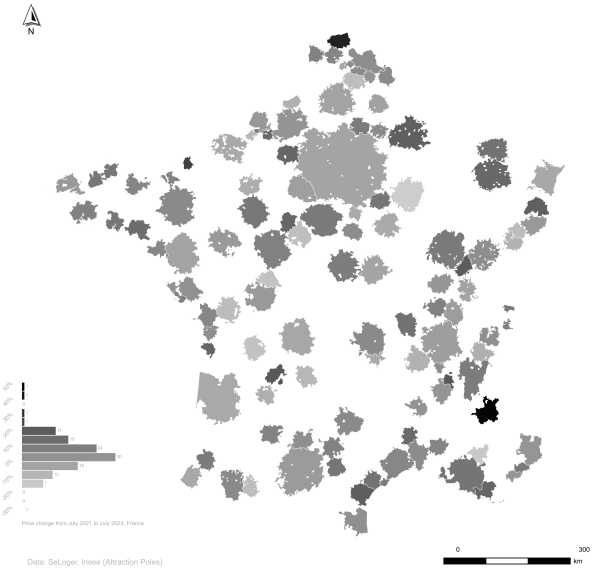
(b) Energy Balanced Houses



(c) Energy Intensive Houses



(d) Houses listed without an EPC score



Note: The maps display the estimated change in the hedonic price of a reference house between July 2021 and July 2024 across INSEE clusters, reported separately by energy-consumption category. Colors indicate the direction and relative intensity of the predicted price variation from our hedonic model. Panels (a)–(d) correspond respectively to energy-efficient, energy-balanced, energy-intensive houses, and listings without an EPC score, illustrating how model-based predicted prices evolved spatially over the period.

5.7 *Anticipatory Effects Discussion*

Figure 22. Set of press articles on subsequent regulation to mandatory disclosure of energy performance

(a) L'opinon (October 2024)



A la surprise générale, Michel Barnier a dit vouloir modifier le calendrier du diagnostic de performance énergétique

Volte-face sur l'interdiction de louer des passoires thermiques

Logement

Dans trois mois, environ 450 000 logements doivent être retirés du marché de la location. Si le calendrier du diagnostic de performance énergétique (DPE) était effectivement assoupli, Michel Barnier suivrait le RN, qui a déposé mi-septembre une proposition de loi pour repousser le délai de trois ans.

Sandra Mathorel

« LE DIAGNOSTIC DE PERFORMANCE énergétique sera simplifié et son calendrier sera adapté. » Une petite phrase et tout un monde est en émoi. A peine une heure après le début de sa déclaration de politique générale, mardi, le Premier ministre aborde l'épineuse question du logement, un sujet très attendu par le secteur. Rappelant que ce dernier est « le premier poste de dépenses des Français », il prend le parti d'annoncer quelques mesures concrètes, dont la réforme du controversé DPE, ce qui sous-tend un probable report de l'interdiction de mise en location des logements les plus énergivores. Une nouvelle, sans surprise, diversement accueillie, selon que la pièce tombe d'un côté ou de l'autre.

« Insécurité ». Côté face, les propriétaires bailleurs, les premiers concernés par le DPE, et les acteurs du logement se réjouissent de cet assouplissement éventuel du calendrier. Créé en 2006, à titre d'abord informatif, le diagnostic de performance énergétique est devenu un critère d'achat et un outil des politiques environnementales. Pour rappel, après analyse d'un diagnostiqueur immobilier, le logement ou l'immeuble est noté de A (maison autronome) à G (passoire thermique). Pour obliger les propriétaires à faire des travaux, la loi Climat et résilience de 2021 a instauré l'interdiction de mettre en location les logements dont l'étiquette énergétique est comprise entre E et G selon un échéancier progressif.

Au 1er janvier 2025, les passoires classées G sont censées ne plus pouvoir être (re)louées. Ce sera ensuite le tour des logements F (au 1er janvier 2028), puis E en 2034. [...] Trois catégories qui représentent une part non négligeable de l'habitat en France ! Sur les 30 millions de résidences principales que compte la France, environ 4,8 millions (*) sont des passoires thermiques (F et G) – soit 15,7% du parc –, dont 1,5 million sont louées par des bailleurs privés. Le risque de voir ces biens sortir du parc locatif, en pleine crise du logement, semble trop important. Juste après la publication de la loi de 2020, le nombre de logements énergivores mis en vente avait bondi en l'espace de quelques mois et représentaient 17% des transactions, constataient les notaires.

« Les propriétaires privés ont conscience depuis longtemps de l'urgence climatique et de la nécessité de rénover. Néanmoins, une nouvelle fois, ils déplorent l'absence de moyens et de temps nécessaires pour répondre à cet objectif », confie à l'Opinion le président de l'Union des propriétaires immobiliers (UNPI), Sylvain Grataloup. « On n'est pas prêts !, renchérit non-homologue de la Fédération nationale de l'immobilier (Fnaim), Loïc Cantin. Au 1er janvier 2025, les propriétaires se retrouveraient dans une inextricable juridique, avec le risque d'être poursuivis par les locataires, qui pourraient réclamer la suspension du loyer et l'obligation de rénover. Il faut prolonger une démarche de conciliation plutôt que de sanction. »

Côté gilet, les acteurs de la rénovation thermique, qui voient le marché à gagner, sont vite montés au créneau, sous couvert de discours emphatiques. « Il serait contraire à l'intérêt général de reporter ces échéances, en particulier pour les locataires qui continueront à souffrir de précarité thermique et financière du fait d'habiter dans une passoire thermique non rénovée », juge Pierre-François Morin, directeur de l'activité Rénovation énergétique d'Hello Watt. Les associations de lutte contre le mal logement, elles, n'ont pas encore réagi.

(*) Au 1er janvier 2023 ; source ministère de la Transition écologique.

la Cour des comptes l'intégrale les politiques publiques de réduction des inégalités d'accès aux soins, les jugeant « fragmentaires », « insuffisamment ciblées » et pas « évaluables ».

Diagonale du vide. Hasard du calendrier, le Conseil national de l'Ordre des médecins a publié mercredi son Atlas de la démographie médicale version 2024. Et la conclusion est sans appel : les inégalités territoriales persistent, et même s'aggravent. Le nombre de médecins, certes, a globalement augmenté, la profession a rajeuni, c'est féminisée... Mais les déserts médicaux, eux, subsistent.

« Les départements hospitalo-universitaires voient leurs effectifs de médecins augmenter et rajeunir (à quelques exceptions près), tandis que les régions périphériques, où la population est plus âgée, subissent une diminution des effectifs médicaux et un vieillissement de leurs praticiens », explique Dr Jean-Marcel Mourgues, vice-président de l'ordre des médecins.

Dans le détail, les départements du centre de la France sont les plus touchés par ces phénomènes médecins généralistes, alors que ceux proches des côtes et des frontières sont les mieux dotés, de même que les grandes villes. Les spécialistes de chirurgicaux, eux, sont particulièrement absents dans les départements du contour du bassin parisien, ainsi que dans les terres.

Entre 2010 et 2024, les diminutions les plus fortes de densité de médecins en activité régulière dessinent une éternelle « diagonale du vide » – 31,5% dans la Creuse, -30% dans la Haute-Marne, 28,7% dans le Cher. A l'inverse, les départements du littoral atlantique, principalement sur les côtes bretonnes, et des frontières suisse et frontalière apparaissent les variations les plus importantes. Plus grave encore, l'Ordre des médecins observe que dans certains départements, en particulier en Ile-de-France, la population augmente... mais le nombre de médecins baisse.

« Résultante d'une inégale répartition géographique des médecins généralistes libéraux, certains territoires se retrouvent dans des contextes de sous-densité médicale où l'offre de soins ne répond pas à la demande et aux besoins de soins des habitants qui y vivent », considèrent les auteurs de l'étude, qui alertent : « Cette situation risquerait de s'aggraver dans les années à venir en raison d'un renouvellement générationnel qui ne s'opère pas en 2024. »

Face à cette tendance lourde, il est à craindre que les « assistants médicaux, les bus de santé, la télésurveillance » ou encore « le recours à l'intelligence artificielle », autres solutions avancées au perchoir par Michel Barnier, soient loin de suffire.

@Jon_Illuiade

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(b) La Tribune (October 2024)



LA TRIBUNE ENTREPRISES ÉDITION NATIONALE MERCREDI 23 OCTOBRE N°7965

DPE : interdire à la location les logements E, F, G divise les députés

Il reste, au 1er janvier 2023, plus de 40% de logements énergivores dans le parc locatif privé. (Photo d'illustration) (Crédits : Andrey Popov - Fotolia.com)

César Armand @Cesarmand

La commission des affaires économiques de l'Assemblée nationale examine, ce mercredi, une proposition de loi visant à abroger le calendrier d'interdiction à la location des passoires thermiques. Sans surprise, le texte ne fait pas l'unanimité auprès des députés.

Le Rassemblement national s'engouffre dans la brèche ouverte par le Premier ministre. Alors que Michel Barnier a annoncé, le 1er octobre, que *« le diagnostic de performance énergétique sera[it] simplifié et son calendrier sera[it] adapté »*, la commission des Affaires économiques de l'Assemblée nationale examine, ce mercredi, un texte du député (RN) de l'Aude Frédéric Falcon visant à abroger le calendrier d'interdiction à la location des passoires thermiques.

« Lorsque j'ai déposé cette proposition de loi il y a plus d'un an, ce n'était pas forcément facile à assumer. J'étais taxé d'an-ti-écolo, mais j'ai été visionnaire: nous avons un vrai problème avec le DPE », se félicite aujourd'hui Frédéric Falcon.

Créé en 2006, le diagnostic de performance énergétique permet d'évaluer la consommation d'énergie d'un logement et son impact en termes d'émissions de gaz à effet de serre. Selon que le logement est classé G, F ou E, il sera impossible de le louer en 2025, 2028 et 2034, en application de la loi Climat et Résilience de 2021. Le DPE est en effet obligatoire pour louer ou vendre un logement. Mais il est critiqué tant par Bercy que par le Conseil d'analyse économique (Matignon).

« Les copros, c'est difficile » (Létard)

Interrogée, le 15 octobre, sur Public Sénat sur ce sujet, la ministre du Logement et de la Rénovation urbaine a promis de *« prendre quelques dispositions législatives, non pas pour supprimer le calendrier des passoires, mais de faire en sorte que de façon très pragmatique, on regarde quelles sont les situations qui ne*

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(c) Les Echos (October 2024)



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Les pistes pour desserrer les contraintes sur les passoires thermiques

IMMOBILIER

« Le diagnostic de performance énergétique sera simplifié, et son calendrier, adapté », s'est engagé le Premier ministre, Michel Barnier.

Les professionnels du secteur avancent leurs propositions.

Elsa Dicharry

Le compte à rebours est lancé. Dès le 1er janvier 2025, les logements classés G au titre du diagnostic de performance énergétique (DPE), soit les plus énergivores et les plus émetteurs de gaz à effet de serre, doivent être interdits à la location. Viendra ensuite le tour des biens F en 2028, puis des E en 2034.

Ces échéances avaient pour but d'activer le lancement de chantiers de rénovation énergétique pour éviter ces interdictions. Mais la mise en œuvre des travaux n'a pas toujours été assez rapide. Et les professionnels de l'immobilier ont alerté à plusieurs reprises sur le risque majeur de voir une multitude de logements sortir du parc locatif dans un contexte où de nombreux Français peinent déjà à se loger.

« Etre pragmatique »

Dès lors, le nouveau gouvernement a promis une réaction rapide. Mais avec quelles conséquences sur le comfort des locataires – qui peuvent souffrir du froid l'hiver et de la chaleur l'été – et la protection de l'environnement ? La Fondation Abbé-Pierre a déjà fait part d'« alertes » à ce sujet.

Et tout cas, le DPE « *sera simplifié et son calendrier sera adapté* », a indiqué le Premier ministre, Michel Barnier, à l'occasion de son discours de politique générale. Une façon pour de remettre en question « *le calendrier global des étiquettes à ce stade, en avançant de l'adapter* [...], avec la *question des copropriétés qui est vraiment au cœur des préoccupations* », a précisé un peu plus tard la ministre du Logement et de la Rénovation urbaine Valérie Létard.

« Deux tiers des logements aujourd'hui en étiquette G et qui ne sont toujours pas requalifiés sont en copropriété. »

VALÉRIE LÉTARD
Ministre du Logement et de la Rénovation urbaine

Au 1er janvier 2023, l'Observatoire de la rénovation énergétique dénombrait près de 1,5 million de passoires énergétiques (logements F et G) dans le parc locatif privé. Photo Laurent Goualard/hans lucas

Rénovation urbaine, Valérie Létard. « *Le Premier ministre essaie d'être tout simplement pragmatique et d'écouter les Français. Deux tiers des logements aujourd'hui en étiquette G et qui ne sont toujours pas requalifiés sont en copropriété* », a-t-elle ajouté.

Il est vrai que, dans les immeubles en copropriété, la rénovation énergétique s'apparente souvent à un véritable parcours d'obstacles. Il faut d'abord obtenir l'accord des copropriétaires sur le sujet – alors qu'un propriétaire de maison est seul à décider, s'avance la ministre.

Demande de clarification

Entre la mise en de la rédaction effective des travaux dans l'immobilier, il peut ainsi se passer plusieurs années. Le temps de trouver une entreprise, de faire valider un devis de cadre des dates de chantier, de trouver les financements, d'obtenir des aides éventuelles... « *Les copropriétés ont du mal à tenir les délais, malgré la bonne foi de la part de propriétaires* », a ajouté Valérie Létard, – qui a promis de « *travailler avec l'ensemble du secteur* » pour trouver des solutions. Certaines propositions sont déjà sur la table. L'Unis – qui représente les syndics de copropriété – comme la FNAIM – pour les agents immobiliers – plaident depuis des mois pour une mesure simple. Il s'agirait de suspendre la possibilité de sanctionner le propriétaire bailleur d'une passoire thermique si les travaux de rénovation énergétique de l'immeuble, sans avoir été déjà réalisés, ont été votés en assemblée générale de copropriété.

Les deux fédérations réclament aussi une clarification sur un sujet essentiel. Les nouveaux baux seront-ils les seuls concernés par l'interdiction, prévue dans seulement quelques semaines, de louer des logements G ? Ou les renouvellements de baux entre locataires reconduction seront-ils également touchés ? « *La loi climat et résilience indique que sont concernés tous les logements loués G au 1er janvier 2025* », estime Loïc Cantin, le président de la FNAIM. Autrement, « *un propriétaire qui avait loué un appartement F ou E au 1er janvier 2025 et, à l'époque où le DPE n'existait pas dans sa version actuelle, qui met* son locataire demander un DPE et, si *son logement est classé G, saisir le juge et réclamer une suspension du versement de ses loyers et la réalisation de travaux* », s'inquiète-t-il.

L'Unis réclame un report de l'échéance de trois ans

L'Unis réclame, de son côté, un report de l'échéance de trois ans, au 1er janvier 2028, s'agissant des reconductions tacites. « *Cela éviterait une entrée en vigueur désordonnée* » de la loi, explique Géraud Debroise, son délégué général. Reste à savoir si ces dispositions peuvent être validées par le Parlement d'ici à la fin de l'année. « *Sans doute pas,* admet Loïc Cantin, *mais il faut déjà un signal politique qui permettra d'apporter de la sérénité.* »

Sylvain Grataloup, le président de l'Union nationale des propriétaires immobiliers (Unpi), reste favorable, de son côté, à une révision du calendrier sur les interdictions à la location des passoires thermiques. « *Il faut inviter les propriétaires à trouver sans avoir ce couperet du 31 décembre* » pour les logements G, estime-t-il. Il rappelle qu'il y a, pour eux, « *des bloqués financiers* ».

Il s'indigne par ailleurs de l'idée que le gouvernement puisse faire un geste uniquement en faveur des locataires et remettre de gaz à effet de serre. Dans le DPE. L'interdiction de louer s'applique déjà aux G », c'est-à-dire les biens qui consomment plus de 450 kWh par mètre carré et par an en énergie finale, et à taux de 1er janvier 2025. Elle touche 5 % des biens en 2028 et les 5 % suivants.

Dans les faits, la mise en application de ces règles patine en raison de nombreux obstacles. Parmi eux, la complexité à cadre réglementaire fluctuant et la méconnaissance des aides publiques comme prévues à la rénovation énergétique. Sans parler du reste à charge souvent rédhibitoire pour certains ménages, des difficultés techniques en copropriété et de la pénurie d'artisans ad hoc, le tout bloquant la réalisation de travaux.

Adoption d'un plan pluriannuel de travaux

Ce parcours du combattant a conduit des propriétaires à vendre leurs passoires thermiques. Ce qui contribue à sanctionner le parc locatif privé, déjà mal en point. Dans ce contexte, nombre d'acteurs ont appelé depuis des mois à un desserrement de ce calendrier contraint. La bonne nouvelle pour les bailleurs, c'est que le nouveau gouvernement de Michel Barnier s'y est dit favorable. Lors de son discours de politique générale, le Premier ministre a indiqué que le DPE « *sera simplifié et son calendrier adapté* ».

Ultérieurement, la ministre du Logement et de la Rénovation urbaine, Valérie Létard, a précisé qu'il ne s'agissait pas de remettre en cause le calendrier global des étiquettes à cet stade qu'il fallait essayer de l'adapter – avec la question des copropriétés qui est vraiment au cœur des préoccupations ». Une étape supplémentaire vient d'être franchie avec l'annonce, dans un certain délai. Le bailleur pourrait dans l'intervalle *continuer à louer son logement G s'il peut produire un procès-verbal de l'Assemblée générale de sa copropriété actant l'adoption de ce PPT* ».

Le nombre de copropriétés concernées est difficilement quantifiable et le délai accordé dépendrait de la durée des travaux dans chaque copropriété. En outre, l'obligation de mettre en place un PPT dans les copropriétés de 50 lots et moins – les plus nombreuses dans le parc collectif total – s'inscrire en vigueur qu'à partir du 1er janvier 2025. Sans que ce chiffre soit connu, on peut imaginer qu'à date très peu d'entre elles ont déjà adopté ce PTT avec engagement de travaux énergétiques.

Autre point positif pour les bailleurs, Valérie Létard a mentionné une possible révision du mode de calcul du DPE, à l'instar de ce qui a été fait pour les petites surfaces, mais cette fois-ci pour mieux prendre en compte les logements chauffés à l'électricité.

Lever l'insécurité juridique

Ces premières pistes du gouvernement sont saluées par les professionnels. Toutefois, ils en attendent plus. Ils réclament notamment une clarification concernant les modalités d'application du couperet du 1er janvier 2025. Selon la loi Climat, le niveau de performance d'un logement décrent est compris « *à compter du 1er janvier 2025, entre la classe A et la classe F* ». Or, et l'application de la loi aux nouveaux contrats conclus à compter du 1er janvier 2025 ne soulève aucune ambiguïté, en revanche quid de la reconduction expresse ou tacite du bail, souvent annuelle ou tous les 3 ans ?

En effet, si elle intervient après la date du 1er janvier 2025, est-ce que la règle s'applique à ces contrats conclus avant ? Et, est-ce le cas immédiatement à compter du 1er janvier 2025 ou au moment où les baux sont renouvelés expressément et/ou tacitement après cette date ?

Les interprétations divergent entre les pouvoirs publics. L'Agence nationale pour l'information sur le logement (Anil) et des juristes. Le flou est tel que le sénateur de l'Eure, Hervé Maurey, dans une question écrite publiée le 17 octobre, interroge le gouvernement sur quelle interprétation il convient de donner à la loi. « *Il s'agit notamment de savoir si, par exemple, un logement de DPE G loué pour une durée de trois ans en décembre 2024 est considéré comme soumis dès le 1er janvier 2025 ou si cette non-décence entrante à partir de la fin du bail, c'est-à-dire le 31 décembre 2027* ».

L'incertitude plonge les bailleurs dans un risque d'insécurité juridique. Le locataire pourrait, à partir du 1er janvier 2025, demander à réaliser un DPE et saisir le juge si son logement est toujours G à compter de cette date afin d'obtenir une suspension de loyer.

Le nombre de copropriétés concernées est difficilement quantifiable.

Lever cette insécurité était justement l'un des objectifs d'une proposition de loi déposée en mai dernier par le député Guillaume Vuilletet. Elle précisait clairement que le calendrier s'appliquait « *aux contrats de locations conclus, renouvelés ou autrement reconduits à compter des dates d'entrée en vigueur de ces obligations* ». Ce qui signifie alors qu'un locataire ne peut signer le 2 janvier 2025 pour un logement classé G. En revanche, il avait signé pour le même bien le classe A et la classe F ». Or, et l'application de la loi aux nouveaux contrats conclus à compter du 1er janvier 2025 ne soulève aucune ambiguïté, en revanche quid de la reconduction expresse ou tacite du bail, souvent annuelle ou tous les 3 ans ?

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Sotheby's veut devenir le temple de la culture et de l'art

(d) Les Echos (October 2024)



Vendredi 25 et samedi 26 octobre 2024 Les Echos 34

Les Echos PATRIMOINE

IMMOBILIER Plus que deux mois et quelques jours avant que les logements étiquetés G dans le diagnostic de performance énergétique ne soient frappés d'indécence et deviennent impropres à la location. Le gouvernement se dit toutefois prêt à assouplir le calendrier.

Vers un sursis pour les locations de passoires thermiques après 2025

Anne-Sophie Vion

Le compte à rebours du calendrier des obligations de rénovation des logements passoires thermiques est enclenché. Dans désormais moins de dix semaines, les logements étiquetés G dans le diagnostic de performance énergétique (DPE) seront frappés d'indécence énergétique et, de facto, interdits à la location. La loi climat et résilience impose aux propriétaires bailleurs de remettre à niveau leurs biens les plus énergivores sous peine de ne plus pouvoir les louer.

Pour mémoire, il s'agit des logements classés G, F et E, sur une échelle qui va de A, pour les plus performants, à G, pour les plus énergivores et émettrices de gaz à effet de serre, dans le DPE. L'interdiction de louer s'applique déjà aux G », c'est-à-dire les biens qui consomment plus de 450 kWh par mètre carré et par an en énergie finale, et à taux de 1er janvier 2025. Elle touche 5 % des biens en 2028 et les 5 % suivants.

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Le poids écrasant des passoires thermiques dans le parc locatif privé

Part des passoires énergétiques (F et G) dans les résidences principales selon le type de logement et le statut d'occupation au 1er janvier 2023, en %

Note de lecture : parmi l'ensemble des résidences principales, 15,7 % sont des passoires ; parmi les appartements du parc locatif privé, 17,1 % sont des passoires.

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